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Planning for a Distributed Disruption: Innovative Practices for Incorporating Distributed Solar into Utility Planning

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Planning for a Distributed Disruption: Innovative Practices for Incorporating Distributed Solar into Utility Planning

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Abstract

The rapid growth of distributed solar photovoltaics (DPV) has critical implications for U.S. utility planning processes. This report informs utility planning through a comparative analysis of roughly 30 recent utility integrated resource plans or other generation planning studies. transmission planning studies, and distribution system plans. It reveals a spectrum of approaches to incorporating DPV across nine key planning areas, and it identifies areas where even the best current practices might be enhanced. 1) Forecasting DPV deployment: Because it explicitly captures several predictive factors, customer-adoption modeling is the most comprehensive forecasting approach. It could be combined with other forecasting methods to generate a range of potential futures. 2) Ensuring robustness of decisions to uncertain DPV quantities: using a capacity-expansion model to develop least-cost plans for various scenarios accounts for changes in net load and the generation portfolio; an innovative variation of this approach combines multiple per-scenario plans with trigger events, which indicate when conditions have changed sufficiently from the expected to trigger modifications in resource-acquisition strategy. 3) Characterizing DPV as a resource option: Today's most comprehensive plans account for all of DPV's monetary costs and benefits. An enhanced approach would address non-monetary and societal impacts as well. 4) Incorporating the non-dispatchability of DPV into planning: Rather than having a distinct innovative practice, innovation in this area is represented by evolving methods for capturing this important aspect of DPV. 5) Accounting for DPV's location-specific factors: The innovative propensity-to-adopt method employs several factors to predict future DPV locations. Another emerging utility innovation is locating DPV strategically to enhance its benefits. 6) Estimating DPV's impact on transmission and distribution investments: Innovative practices are being implemented to evaluate system needs, hosting capacities, and system investments needed to accommodate DPV deployment. 7) Estimating avoided losses associated with DPV: A time-differentiated marginal loss rate provides the most comprehensive estimate of avoided losses due to DPV, but no studies appear to use it. 8) Considering changes in DPV's value with higher solar penetration: Innovative methods for addressing the value changes at high solar penetrations are lacking among the studies we evaluate. 9) Integrating DPV in planning across generation, transmission, and distribution: A few states and regions have started to develop more comprehensive processes that link planning forums, but there are still many issues to address.

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Acronyms and Abbreviations

AC Alternating current
AEO Annual Energy Outlook
APS Arizona Public Service

BNEF Bloomberg New Energy Finance
BPP Bundled Procurement Plan

CAISO California Independent System Operator

CEC California Energy Commission
CEM Capacity-expansion model

CO₂ Carbon dioxide

CPUC California Public Utilities Commission

DC Direct current

DEC Duke Energy Carolinas
DEI Duke Energy Indiana
DEP Duke Energy Progress
DER Distributed energy resources

DERAC Distributed Energy Resources Avoided Cost Calculator

DG Distributed generation

DOM Dominion

DPV Distributed photovoltaics
DRP Distribution resources plan
DSM Demand-side management
EDD Electrical Distribution Design

EE Energy efficiency

EIA U.S. Energy Information Administration

ELA Entergy Louisiana

ELCC Effective load-carrying capability

FiT Feed-in tariff

FPL Florida Power & Light
GPC Georgia Power Company
HECO Hawaiian Electric Companies

ILR Inverter loading ratioIPC Idaho Power CompanyIRP Integrated resource planISO Independent system operator

ISO-NE ISO New England ITC Investment tax credit

LADWP Los Angeles Department of Water and Power

NEM Net energy metering

NREL National Renewable Energy Laboratory

NSP Northern States Power

NVP Nevada Power

NWPCC Northwest Power and Conservation Council
NYISO New York Independent System Operator
NY REV New York Reforming the Energy Vision

OER Office of Energy Resources

PAC PacifiCorp

PG&E Pacific Gas & Electric

PNM Public Service of New Mexico

PSE Puget Sound Energy

PSIP Power Supply Improvement Plan

PV Photovoltaic(s)

PVRR Present value of the revenue requirement

RIM Ratepayer Impact Measure RPS Renewable portfolio standard SCE Southern California Edison

SCT Societal Cost Test

SDG&E San Diego Gas & Electric

SMUD Sacramento Municipal Utility District
SREC Solar Renewable Energy Credit
T&D Transmission and distribution

TEP Tucson Electric Power

TGT Tri-State Generation and Transmission

TRC Total Resource Cost Test
TVA Tennessee Valley Authority

UCT Utility Cost Test
UPV Utility-scale PV

WECC Western Electricity Coordinating Council

Executive Summary

Analysts project that distributed solar photovoltaics (DPV) will continue growing rapidly across the United States. This growth has critical implications for utility planning processes, potentially affecting the size and type of future infrastructure needs as well as the solution set for meeting those needs. Developing appropriate techniques for incorporating DPV's unique characteristics into utility planning processes—across generation, transmission, and distribution—is therefore essential to ensuring reliable operation of the electric system at least cost. It is also paramount to ensuring that the costs and benefits of DPV resources are fully and accurately valued, because that value may derive in large part from investments that utilities make or avoid owing to needs identified within their planning studies.

With this report, we seek to inform utility planning through a comparative analysis of roughly 30 recent utility integrated resource plans or other generation planning studies, transmission planning studies, and distribution system plans. The rapid growth of DPV has not been distributed equally across U.S. utility territories, and the same is true for projected future growth. While some of the studies we review forecast 2020 DPV penetrations equivalent to 5% or more of retail sales, fewer than half consider penetrations beyond 1% by 2020. Thus it is unsurprising that utilities and other planning organizations have differed in their perceptions about the need to incorporate DPV into resource and transmission and distribution (T&D) plans. Because of this staggered progress, organizations that are just beginning to address DPV can draw on innovative practices from organizations that already are incorporating DPV rigorously into their plans. Our report reveals this spectrum of approaches across nine key planning areas, and it identifies areas where even the best current practices might be enhanced.

Below we summarize current practices and highlight approaches that are innovative and potentially worthy of emulation. We conclude with a brief discussion of future work.

Developing a Forecast of DPV Deployment

The main forecasting approaches across the studies we analyze include stipulated forecast, historical trend, program-based approach, and customer-adoption modeling. About 70% of relevant studies employ one or more of the first three approaches, which rely on few or no quantifiable predictive factors. In contrast, customer-adoption modeling explicitly uses historical DPV deployment, location-specific DPV technical potential, various DPV economic considerations, and end-user behaviors as predictive factors (Figure ES-1). A quarter of the studies use this innovative method, including those by the Northwest Power and Conservation Council, PacifiCorp, Pacific Gas & Electric (PG&E), Puget Sound Energy (PSE), and the Western Electricity Coordinating Council. Though our analysis suggests various ways to improve current customer-adoption models, these models represent the most comprehensive forecasting approach available today.

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¹ We consider DPV to include PV systems that are relatively small (less than 5 MW), connect to the distribution system, and are either in front of or behind the meter.

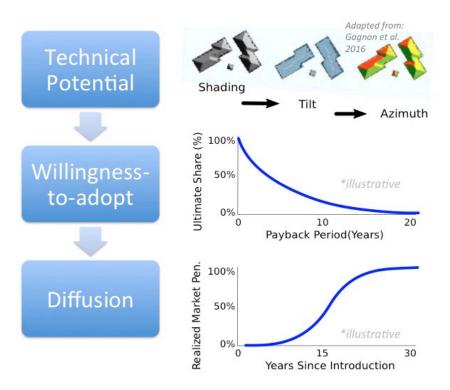
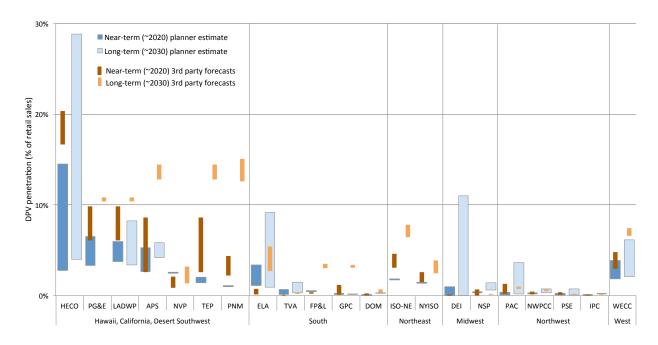


Figure ES-1. Process Commonly Used to Develop Customer-Adoption Models

The quantities and ranges of DPV deployment forecasted in the studies we analyze vary by region, utility, and forecasting method (Figure ES-2). A number of utilities use only a single DPV forecast or consider only a small range. Stipulated forecasts generally have the largest ranges, whereas program-based forecasts tend to have small ranges, and the high end of third-party forecasts is above the high end of utility planning forecasts about two thirds of the time. Our analysis suggests that combining various DPV forecasting methods could be valuable. Such an approach might use program goals discounted for uncertainty as lower bounds, customer-adoption models to forecast expected levels, and third-party forecasts and stipulated what-if scenarios to explore the full range of plausible futures.



Note: Additional detailed notes explaining this figure are in the main report (Section 3.4). For full organization names, see "Acronyms and Abbreviations" above.

Figure ES-2. Utility DPV Forecasts in the Near Term and Long Term Compared with Third-Party DPV Forecasts

Ensuring Robustness of Decisions to Uncertainty in DPV Quantity

Robustness of decisions to uncertainty in DPV adoption is most clearly addressed in utility integrated resource planning, with some consideration in transmission planning and little in distribution planning. The relevant studies we review use one of three methods to address uncertainty: single forecast (33% of studies), subject to sensitivity (11%), and per-scenario plan (56%). The per-scenario plan method often uses a capacity-expansion model (CEM) to develop least-cost plans for various scenarios, including different levels of DPV adoption (Figure ES-3). Because it accounts for changes in both net load and the generation portfolio, this is the most comprehensive of the three methods. An innovative variation of this approach—acquisition path analysis—combines multiple per-scenario plans with trigger events, which indicate when conditions have changed sufficiently from the expected to trigger modifications in resource-acquisition strategy. PacifiCorp and Hawaiian Electric Companies (HECO) use variations of this approach in their resource planning.

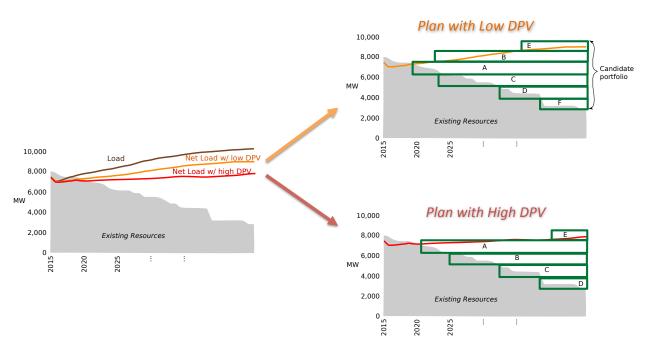


Figure ES-3. Illustration of Process for Developing Per-Scenario Plans

Characterizing DPV as a Resource Option

Fewer than half of the studies we review evaluate DPV as a resource that could be proactively deployed to meet future needs. Those that do consider DPV as a resource use various approaches to determine if it should be part of the plan. The two most common are to compare the performance of candidate portfolios with varying quantities of DPV and to develop minimum-cost portfolios via CEMs with DPV as a resource option. Regardless of the characterization method used, the ways DPV is distinguished from other resource options are important. Some utilities dismiss DPV based only on its higher cost and lower capacity factor relative to utility-scale PV (UPV). However, DPV's capacity credit as well as the avoided losses, transmission deferrals, and distribution-system cost impact associated with DPV also can be significant (Table ES-1). PG&E's plan stands alone among the utility resource plans we review in accounting for all these factors, which are also important for the locational net benefits methodology in the California Distribution Resources Plans and the New York Reforming the Energy Vision (NY REV) process.

Table ES-1. Characteristics Used to Distinguish DPV from UPV or Other Resource Options

Plan*	Characteristi	ic				
	Capital Cost of DPV vs. UPV	Capacity Factor of DPV vs. UPV	Capacity Credit of DPV vs. UPV	Avoided Losses	Transmission Deferral	Distribution Deferral
DEI (2015)	X					
GPC (2016)				X	X	
HECO (2013)	X	X				
IPC (2015)			X			
LADWP (2014)	X				X	
NWPCC (2016)	X	X	X	X		
NSP (2015)	X	X	X	X		
PG&E (2014)	X	X	X	X	X	X
PSE (2015)	X		•		X	
TVA (2015)	X					

^{*}Plan references are in Appendix A. For full organization names, see "Acronyms and Abbreviations" above.

Incorporating the Non-Dispatchability of DPV into Planning Methods

Rather than a distinct innovative practice for incorporating the non-dispatchability of DPV in planning, innovation in this area is represented by evolving methods for capturing this important aspect of DPV. Hourly DPV generation profiles allow for some potential integration issues to be included when evaluating portfolios with DPV, including multi-hour ramping impacts and overgeneration. Most planning studies in our sample appear to use an hourly DPV profile. Impacts of DPV that are not captured with hourly generation profiles, such as sub-hourly variability and uncertainty, can be addressed through detailed integration studies. Various studies quantify the operational integration costs of solar, suggesting a range of \$0.5-\$10/MWh (for all solar, not just DPV). The methods used to estimate DPV's capacity credit vary and are not always described. A few utilities use detailed reliability-based models to estimate DPV's effective load-carrying capability, whereas others use less-rigorous methods to estimate capacity credit. Among the other integration-related issues discussed in the studies, the Los Angeles Department of Water and Power (LADWP) highlights the overgeneration potential of low-load spring days and considers mitigation via electric vehicle (EV) charging during these periods. Combining hourly DPV profiles with detailed production cost models can help in evaluating the role of EVs and other technologies and in identifying times when overgeneration may be a concern

Accounting for Location-Specific Factors of DPV

Transmission and distribution planning studies require projections of DPV locations. We identify three methods for estimating future locations: proportional to load (40% of relevant studies), proportional to existing DPV (40%), and propensity to adopt (30%).² The first two methods proportionally allocate DPV deployment based on the locations of existing load, population, or DPV. The propensity-to-adopt method employs additional predictive factors as well, such as demographics and customer load. Utilities that use this innovative analysis include PG&E,

² One study uses both propensity to adopt and proportional to existing DPV.

Southern California Edison, and Sacramento Municipal Utility District. Another emerging utility innovation is locating DPV strategically to enhance its benefits. Organizations exploring this tactic include Duke Energy Indiana, Dominion, PG&E, Georgia Power Company, and ISO New England—generally focusing on utility-owned systems. A recent pilot project in Rhode Island demonstrates how promotion of strategic locations for behind-the-meter DPV can help defer feeder upgrades.

Estimating the Impact of DPV on T&D Investments

Innovations in estimating the impact of DPV on T&D investments apply differently to different organizations, depending on each organization's current progress in this area as well as its projected DPV deployment and the robustness of its T&D infrastructure. For organizations that have not yet considered DPV in T&D studies, innovative examples of such planning are available from numerous planning entities. Likewise, organizations that find themselves needing to calculate hosting capacity—the amount of DPV that can be interconnected to the distribution system without violating operating limits—can draw on innovative studies from their peers. These include the use of hosting capacity analysis to both screen and steer the location of DPV. At the most advanced end of the spectrum, some organizations are already proactively planning investments to accommodate additional DPV. Innovative analyses by Pepco, Dominion/Navigant, and HECO calculate the cost of various options for increasing hosting capacity, including the impacts of advanced inverters and energy storage.

Estimating the Avoided Losses Associated with DPV

Of the studies we review that mention avoided losses due to DPV and provide sufficient detail, we observe three methods to account for these losses: average loss rate (60% of studies), time-differentiated average loss rate (30%), and detailed analysis of losses (10%). Because of the non-linear variation of line losses with load, the most comprehensive estimation of system losses—and thus the potential avoided losses with DPV—is a time-differentiated marginal loss rate. However, none of the studies we evaluate appear to use a marginal loss calculation. This represents an area for future innovation. The one detailed circuit-level analysis of losses, by PSE, offers a different refinement at a relatively small scale.

Considering Changes in Costs and Benefits of DPV with Higher Solar Penetration

Perhaps because few utilities expect high penetrations of solar in the near future, innovative methods for addressing the value changes at such penetrations are lacking among the studies we evaluate. Georgia Power Company's avoided cost of DPV calculations estimate the incremental avoided cost for tranches of DPV, though some details are redacted. Many utilities employ production cost models, and these tools can be used to show changes with increasing solar penetration. CEMs could also account for changes in the costs and benefits of DPV with higher penetration, though some models may need to be modified to account for changes in the capacity credit with higher penetration. In addition, none of the studies mention changes in avoided losses with higher solar penetration.

One complicating factor is that the change in value with penetration may depend on other external factors. LADWP, for example, highlights that EV charging during the day may mitigate some of the challenges with overgeneration. Customer adoption of EVs and their preferences for charging the EVs may therefore affect the value of DPV at high penetration. Given uncertainty in

how customer preferences and other factors may change over time, scenario analysis and analysis of the robustness of decisions may be helpful to decision makers.

Integrating DPV in Planning across Generation, Transmission, and Distribution Fully integrating DPV into planning requires a more comprehensive approach in which distribution, transmission, and resource planning are more tightly linked. A few states and regions—including California, New York, and New England—have started to develop these more comprehensive processes, but there are still many issues to address. Understanding the range of different approaches across the United States and highlighting innovative practices should help accelerate those changes.

Future Research

With future research, we will analyze whether some of the innovative practices identified here can meaningfully affect planning study results. Of particular interest are innovative practices for forecasting DPV adoption, examining the robustness of decisions to DPV uncertainty, and considering DPV as a resource.

1. Introduction

Analysts project that distributed solar photovoltaics (DPV) will continue growing rapidly across the United States (BNEF 2015; GTM Research and SEIA 2015, 2016; Gagnon and Sigrin 2016).³ This growth has critical implications for utility planning processes, potentially affecting the size and type of future infrastructure needs as well as the solution set for meeting those needs. Developing appropriate techniques for incorporating DPV into utility planning processes—across generation, transmission, and distribution—is therefore essential to ensuring reliable operation of the electric system at least cost (Newcomb et al. 2013, Wiedman and Beach 2013, Hoke and Komor 2012). It is also paramount to ensuring that both the costs and benefits of DPV resources are fully and accurately valued, as that value may derive in large part from investments that utilities make (or avoid) as a result of needs identified within their planning studies.

The unique characteristics of DPV, however, present a variety of challenges within the context of utility planning. For example, DPV deployment is often driven by individual customers' decisions to adopt, rather than by identified system needs. In addition, DPV is located near loads, which offers potential cost savings from avoided losses and deferral of transmission and distribution (T&D) investments (Cohen et al. 2016), but two-way flows may require upgrades to distribution systems (Lindl et al. 2013). And, as with other non-dispatchable resources, variability and uncertainty in DPV output may require greater system flexibility and limit the contribution of DPV to resource adequacy.

Given the above challenges and the relatively recent growth of DPV, current practices surrounding the treatment of DPV in utility planning studies are still rapidly evolving. With our research, we seek to inform utility planning through a comparative analysis of roughly 30 recent utility integrated resource plans (IRPs) or other generation planning studies, transmission planning studies, and distribution system plans. We benchmark current practices across nine key methodological areas related to the treatment of DPV (Figure 1). Some issues, such as a trend toward bundling DPV with other enabling technologies like storage or load control, are crosscutting and impact multiple methodological areas. Our intent is both to characterize the range of current practices and to highlight new and innovative practices, which utility planners and regulators can reference as they refine their planning studies. Future research will explore how effectively incorporating DPV into planning studies can meaningfully affect the outcome of the plan, in terms of total resource costs and potential impact on solar deployment.

The present study builds upon the existing body of literature on utility resource planning practices, including other comparative analyses of utility IRPs evaluating the treatment of solar and other renewables (Wiser and Bolinger 2006, Mills and Wiser 2012a, Sterling et al. 2013), energy efficiency (EE) (National Action Plan for Energy Efficiency 2007, Hopper et al. 2009, Lamont and Gerhard 2013, Takahashi 2015), and environmental regulatory risk (Barbose et al. 2008, Luckow et al. 2015, Wilson and Biewald 2013, Wilkerson et al. 2014). Beyond utility IRPs, other studies have focused on non-wires alternatives within transmission planning, partly

³ We consider DPV to include PV systems that are relatively small (less than 5 MW), connect to the distribution system, and are either in front of or behind the meter.

in response to planning requirements imposed by Federal Energy Regulatory Commission Order 1000 (Hempling 2013, Neme and Grevatt 2015, Stanton 2015, Watson and Colburn 2013), while recent attention has turned to the impacts of distributed energy resources (DER) on the distribution system and associated planning processes (Colman et al. 2016, SolarCity 2015, Edge et al. 2014, Lindl et al. 2013, EQL Energy 2015, De Martini and Kristov 2015, Palmintier et al. 2016). Finally, though this study is not focused on the value of solar, per se, we evaluate current planning practices partly by how they account for the myriad potential sources of DPV value, drawing from the extensive value-of-solar literature (Denholm et al. 2014, Keyes and Rábago 2013, Hansen et al. 2013).⁴

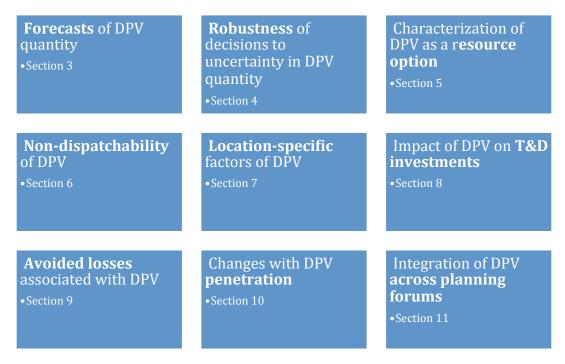


Figure 1. Methodological Elements of Planning Studies Addressed in Each Section

We describe the planning documents included in our review in Section 2. We then address each of the nine methodological issues in turn: forecasting the quantity of DPV (Section 3), ensuring robustness of planning decisions to uncertainty in the quantity of DPV (Section 4), characterizing DPV as a resource option (Section 5), incorporating non-dispatchability of DPV in planning studies (Section 6), accounting for location-specific factors of DPV (Section 7), estimating the impact of DPV on T&D investments (Section 8), estimating avoided losses associated with DPV (Section 9), considering changes in costs and benefits with higher solar penetration (Section 10), and integrating DPV across different planning forums (Section 11). In each of these sections, we introduce the methodological element by postulating a motivating question that might be asked by a planner. We then summarize the range of approaches observed in the planning documents and highlight new and innovative practices. Finally, in Section 12, we summarize innovative practices that might improve the representation of DPV in planning studies, and we discuss areas for future work.

⁴ Numerous state-specific value-of-solar studies are tracked here: http://www.seia.org/policy/distributed-solar/solar-cost-benefit-studies.

2. Planning Documents Included in Review

The documents included in this review focus on power system planning in which, ideally, the outcome of each document is a recommendation for a preferred set of investments or strategy for making investments.

We applied additional broad criteria to select our sample of planning documents. All of the studies are recent (completed since 2013) and explicitly include DPV to some extent. All are publicly available such that major assumptions, methods, and recommendations are available to the public, even if proprietary tools/models are used in the process. Nearly all also involve key decision makers, in that participants or leaders of the planning process have the authority and ability to act based on plans.⁵ Finally, though we sought to include a broad and representative range of studies, we did not comprehensively review all relevant planning studies.

We include three primary types of planning documents: IRPs, transmission plans, and distribution system plans. We list the individual studies below and provide additional information in Appendix A.

The goal of IRPs is to identify generation- and demand-side measures that can meet projected energy and capacity needs, often in a least-cost manner, though objectives such as mitigating risk, achieving energy policy goals, and mitigating environmental impact are also considerations. Within IRPs, DPV has two potential roles: (1) customer adoption of DPV can reduce energy and capacity needs, and (2) DPV can be part of preferred portfolios to meet needs. The IRPs included in our review are listed in Table 1. The overall objectives of IRPs are somewhat standard, though the amount of detail and role of DPV varies considerably across these studies. We also include two studies that are not traditional IRPs: Pacific Gas & Electric's (PG&E's) *Bundled Procurement Plan* (BPP) and the *Seventh Conservation and Electric Power Plan* from the Northwest Power and Conservation Council (NWPCC).

Table 1. IRPs Included in Review

Entity	Title and Year
Arizona Public Service (APS)	2014 Integrated Resource Plan
Dominion (DOM)	2015 Integrated Resource Plan
Duke Energy Carolinas/Progress (DEC/DEP)	2014 Integrated Resource Plan
Duke Energy Indiana (DEI)	2015 Integrated Resource Plan
Entergy Louisiana (ELA)	2015 Integrated Resource Plan
Florida Power & Light (FPL)	Ten Year Power Plant Site Plan: 2015–2024
Georgia Power Company (GPC)	2016 Integrated Resource Plan

3

⁵ The Western Electricity Coordinating Council (WECC) and NWPCC do not have clear authority or ability to act on their plans, but their planning results are often very influential in other decision-making forums.

Hawaiian Electric Companies (HECO) ^{6,7}	2013 Integrated Resource Planning Report
Idaho Power Company (IPC)	2015 Integrated Resource Plan
Los Angeles Department of Water and Power (LADWP)	2014 Integrated Resource Plan
Nevada Power (NVP)	2015 Integrated Resource Plan
Northern States Power (NSP)	2015 Resource Plan
Northwest Power and Conservation Council (NWPCC)	Seventh Conservation and Electric Power Plan (2016)
Pacific Gas & Electric (PG&E)	2014 BPP
PacifiCorp (PAC)	2015 Integrated Resource Plan
Public Service of New Mexico (PNM)	2014 Integrated Resource Plan
Puget Sound Energy (PSE)	2015 Integrated Resource Plan
Tennessee Valley Authority (TVA)	2015 Integrated Resource Plan
Tri-State Generation and Transmission (TGT)	2015 Integrated Resource Plan/Electric Resource Plan
Tucson Electric Power (TEP)	2014 Integrated Resource Plan

The goal of the transmission planning studies is to identify transmission investments for reliability, economic, or public policy reasons. In addition, some of the transmission planning entities conduct capacity market auctions or assessments to ensure adequate resources will be available to meet reliability needs. Within transmission studies, DPV has two potential roles: (1) it can impact the need for new transmission or other capacity, and (2) it can be a substitute for transmission assets by meeting the same needs (i.e., it can be a non-transmission alternative). The transmission planning documents included in our review are listed in Table 2. In addition, some of the IRPs in the previous table include transmission assessments (e.g., HECO's IRP).

Table 2. Transmission Plans Included in Review

Entity	Title and Year
California Independent System Operator (CAISO)	2015–2016 Transmission Planning Process Unified
	Planning Assumptions and Study Plan
ISO New England (ISO-NE)	2015 Regional System Plan
New York Independent System Operator (NYISO)	2015 Load and Capacity Data Report: "Gold Book"
РЈМ	2015 Regional Transmission Expansion Plan
Western Electricity Coordinating Council (WECC)	Integrated Transmission and Resource Assessment:
	Summary of 2015 Planning Analyses

The goal of distribution plans is to ensure adequate distribution infrastructure, though the documents included in this review focus much more on process, and revisions to that process in the face of growing interest in DER like DPV, rather than on specific investment decisions.

⁶ Hawaiian Electric Companies includes three companies: Hawaiian Electric Company, Hawaii Electric Light Company, and Maui Electric Company. For convenience we collectively refer to these companies as HECO.

⁷ HECO also recently filed a "Power Supply Improvement Plan" that much more tightly couples customer adoption of DPV with the analysis. Where relevant we note the particularly innovative practices employed in the more recent plan.

Within the distribution studies, DPV has two primary roles: (1) deployment of DPV can impact the need for distribution system upgrades, and (2) DPV can substitute for new distribution infrastructure. The distribution planning documents included in our review are listed in Table 3.

Table 3. Distribution Plans Included in Review

State and Entity	Title and Year
California: PG&E	2015 Distribution Resources Plan (DRP)
California: Southern California Edison (SCE)	2015 DRP
California: San Diego Gas & Electric (SDG&E)	2015 DRP
Hawaii: HECO	2014 Distributed Generation Interconnection Plan
Hawaii: HECO	2015 Circuit-Level Hosting Capacity Analysis
Massachusetts: National Grid	2015 Grid Modernization Plan
New York: New York Department of Public Service	2015 Distributed System Implementation Plan Guidance

3. Developing a Forecast of DPV Deployment

Planner's question: How do you forecast future customer adoption of DPV?

The future quantity of DPV is driven, at least partially, by customer decisions to adopt DPV that are beyond the control of utility planners. The rate of adoption depends on many factors, some of which are changing rapidly, including the upfront cost of DPV systems, availability and level of incentives, and retail rate designs or net-energy-metering policies that affect the bill savings from customer-sited photovoltaics (PV). These changes in the drivers of DPV adoption increase the challenge of forecasting DPV installations.

In this section, we summarize the range of approaches utilities use to create DPV forecasts⁸ and the drivers utilities consider in making those forecasts. We also compare DPV forecasts from utilities to forecasts from third parties, highlighting regional trends and the impact of forecasting methodology. One nascent development in forecasting DPV is the use of customer-adoption models. We summarize some of the advances in customer-adoption models that may improve upon the approaches used in practice. In this section we focus only on forecasting the quantity of DPV. Approaches to forecasting the location of DPV, of particular interest in T&D planning, are discussed in Section 7.

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⁸ Though some utilities also had separate forecasts for other DER, none except TGT explicitly forecast adoption of DPV bundled with other enabling technologies like storage or load control.

Innovative Forecasting: Customer-Adoption Models

Because the future is inherently uncertain, the predictive accuracy of methods that forecast DPV deployment far into the future cannot be evaluated directly in the present. That said, the types and importance of predictive factors accounted for in various methods can be compared (Table 4). A large portion of DPV deployment is based on customer-adoption decisions, which makes customer-adoption models an important innovation for forecasting DPV deployment. Customer-adoption models explicitly use historical DPV deployment, location-specific DPV technical potential, various DPV economic considerations, and end-user behaviors as predictive factors. Organizations that use this approach include NWPCC, PAC, PG&E, PSE, and WECC, as described in Section 3.2.

Table 4. Predictive Factors Used by Various Forecasting Methods

Method	Description	Predictive Factors Used				
		Recent installation rates	Incentive program targets	Technical potential	PV economics	End-user behaviors
Stipulated Forecast	Assumes end-point DPV deployment					
Historical Trend	Extrapolates future deployment from historical data	X				
Program- Based Approach	Assumes program deployment targets reached		X			
Customer- Adoption Modeling	Uses adoption models that represent end-user decision making	X		X	X	X

3.1 Forecasting Approaches

Approaches used to forecast DPV deployment vary greatly in the planning studies analyzed. We group these approaches under five categories:

- Customer-adoption modeling: DPV forecasts are determined using adoption models designed to represent end-user decision making based on PV economics, resource potential, diffusion, and other factors. Five of the planning studies explicitly use this approach as detailed in Section 3.2.
- *Program-based approach:* DPV deployment is assumed to reach predetermined incentive program targets. Six of the planning studies examined use this approach. One example is TEP, which is required to use distributed generation (DG) to meet 30% of the overall 15% Arizona renewable portfolio standard (RPS) by 2025. As another example, ISO-NE relies on state PV policy goals (e.g., state-specific Solar Renewable Energy Credit

⁹ Of the DG, 90% is DPV, and the rest is solar hot water.

- [SREC] goals and other incentive programs, net energy metering [NEM] caps, etc.) to inform its forecasts. 10
- Stipulated forecast: End-point DPV deployment levels are assumed, sometimes at the extremes of plausible futures, and impacts are evaluated based on these assumed levels. Seven reviewed planning studies use this approach. Usually no further detail is provided to explain how planners came up with their forecast. In some cases, stipulated "what-if scenarios" are used to test the robustness of additional planning decisions to high levels of DPV, as shown in the case of DEI, HECO, and TGT as detailed in Section 4.
- *Historical trend:* Extrapolations from historical data are used to forecast future DPV deployment. These forecasts are typically based upon recent installation rates, where the data are often sourced from local PV incentive programs (e.g., NVP and PG&E). Planned (queued) projects can also inform expected trends (e.g., HECO).
- Other: Methods that differ from those listed above or are unspecified, often based on the judgment of the planners, are employed. These include one planning study with an unclear DPV forecasting method (DEC/DEP), one study that uses a proprietary third-party forecast (PJM), and one study by TVA that ties its forecast to outcomes from similar scenarios in the U.S. Energy Information Administration's (EIA's) Annual Energy Outlook (AEO). DPV penetration is small and stagnant in TVA's "Current Outlook" reference scenario, while the "Distributed Marketplace" scenario has more substantial growth (with DPV accounting for about 1% of retail sales in 2025).

Table 5 summarizes the DPV forecasting approaches from the studies analyzed. Overall, the above five categories demonstrate a wide range of DPV forecasting approaches presently being used. In part, this diversity reflects the degree to which utility incentive programs are needed to drive DPV markets. Program goals are suitable for forecasts when specific incentive programs are required to drive the market, but not when substantial adoption occurs without programs. When program goals do not drive DPV adoption, DPV deployment is highly sensitive to the customer economics of DPV. By including customer economics as a determinant of DPV

¹⁰ ISO-NE applies a discount factor to far-future projections to account for forecasting uncertainties. For example, the initial projections based on state goals are discounted by 5% for 2015 and 2016, with an increase in the discount to 15% in 2017 owing to uncertainty about PV deployment after—at the time the forecast was developed—the federal investment tax credit (ITC) was expected to expire. The discount rates then increase to 25% by 2019. Beyond the end date of a state's policy goal, ISO-NE assumes DPV adoption will continue at a level that is 50% of the adoption rate prior to the end date of the policy. This approach is a simple means of capturing uncertainty associated with future expansion of state policies and/or future market conditions while acknowledging some degree of PV growth is expected to continue even after the end of state policies.

¹¹ The different DPV forecasts are created for each scenario by matching TVA scenarios to scenarios in EIA's AEO (2013) based on the degree of carbon dioxide (CO₂) regulation in the respective scenarios. TVA then uses outcomes of the EIA scenarios to determine scenario-specific national renewable deployment rates, and it makes scenario-specific assumptions about what fraction of the national renewable energy deployment is due to customer adoption of DPV. For example, 11% of the national renewable energy growth is assumed to come from DPV in the "Current Outlook" scenario, whereas 50% comes from DPV in the "Distributed Marketplace" scenario. Finally, TVA assumes that TVA customers will adopt DPV at a rate of 75% of the national average. The key factors that drive differences in the DPV forecasts across scenarios are (1) CO₂ regulations (more stringent regulations increase DPV adoption up to a point, though "De-carbonized Future" assumes a larger fraction of renewable energy growth is from utility-scale renewables), (2) customer preferences (DPV adoption is higher in the "Distributed Marketplace" scenario), and (3) economic growth conditions (DPV adoption is higher in "Growth Economy" than in "Stagnant Economy").

deployment, models can directly represent DPV sensitivity to rate restructuring, NEM extension, and other singular events (e.g., renewal of the federal ITC).

Table 5. Approaches to Forecasting DPV in Planning Studies

Plan	Approach	Details	
APS 2014 IRP	Program-based and stipulated	Assumes compliance with Arizona's Renewable Energy Standard (15% renewable by 2025, with 30% coming from DG) in the base forecast. Assumes higher DER adoption in an "Increased Environmental Policy" scenario.	
DOM 2015 IRP	Program-based	Uses a 30-MW-by-2016 Solar Partnership Program goal for utility-owned DPV on leased commercial and industrial customer property and in community settings. Other programs (i.e., Solar Purchase Program and NEM) are mentioned, but no forecast is specified.	
DEC/DEP 2014 IRP	Other	Uses a single forecast of behind-the-meter rooftop PV to create an hourly net-load forecast. The method used to create the forecast is not clear from the IRP or other supporting documents.	
DEI 2015 IRP	Stipulated	Includes an "Increased Customer Choice" scenario based on stakeholder comments in which DPV provides an additional 1% of load per year beginning in 2020.	
ELA 2015 IRP	Historical trend and stipulated	Uses a forecast based on a 12-month average of installation rates and average system size. No additional growth is assumed after 2017 owing to the ITC expiration. Also uses higher "Distributed Disruption" scenario that assumes continued state policy support for DG.	
FPL 2015 Ten Year Plan	Stipulated	Assumes 444 GWh/year above 2014 levels by 2024.	
GPC 2016 IRP	Program-based	Uses the Renewable Energy Development Initiative, which establishes a program goal of 50 MW of DPV (smaller than 3 MW) that is competitively bid and an additional 50 MW of customer-sited DPV that is paid a fixed price by 2019.	
HECO 2013 IRP	Historical trend and stipulated 12	Grounds the base forecast for new installations on historical installations, current growth rates, known projects in queue, and likely projects planned by large customers. HECO also gathered information on future customer projects from utility discussions with customers about their future plans. They also include different DPV deployment rates in several what-if scenarios.	
IPC 2015 IRP	Stipulated	Assumes an existing 4 MW of NEM customers with an additional ~4 MW of DPV per year after 2022 in one stakeholder-driven scenario.	
ISO-NE 2015 Regional Plan	Program-based	Translates individual state-by-state policy goals, largely incentive programs or NEM caps, into capacity estimates: SREC II in Massachusetts (1,600 MW $_{\rm DC}$ by 2020), ZREC program in Connecticut (323 MW from 2015–2020), and REG program (160 MW by 2019) and NEM program in Vermont (until 15% of peak load NEM cap is reached), etc. ISO-NE contracted ICF to identify economic drivers affecting the potential development of PV in the region (ICF International 2015). ISO-NE's forecast is also informed by historical trends.	
LADWP 2014 IRP	Program-based	Uses separate capacity goals for three incentive programs by 2020: feed-in tariff (FiT, 450 MW), NEM (310 MW), and community solar (40 MW).	

¹² In its 2016 Power Supply Improvement Plan (PSIP), HECO uses a customer-adoption model for DPV from Boston Consulting Group.

NVP 2015 IRP	Historical trend	Bases forecast on trends in installations observed in 2014 for the SolarGenerations rebate program along with non-rebated PV that is still eligible for NEM. The forecasts are created for residential as well as small and large commercial and industrial customer classes. The rate of DPV growth is assumed to decrease after the assumed step-down of the ITC after 2016.	
NWPCC 7 th Power Plan	Customer-adoption modeling	Integrates the DPV forecast with the demand forecast using a multinomial logit customer choice model that weighs preferences for grid electricity vs. electricity from DPV. The model estimates customer preferences (including non-economic factors) for solar based on historical relationships between retail rates, solar cost performance, and customer adoption. The forecast is then based on projections o future rates and PV cost and performance. A projected installed capacity of 100 MW _{AC} in 2015 increases to 500 MW _{AC} in 2035.	
NSP 2015 Resource Plan	Program-based	Uses Minnesota's requirement that utilities supply 10% of retail load from solar resources by 2030, of which 10% is to come from smaller DPV systems (under 20 kW_{DC}).	
NYISO 2015 Gold Book	Stipulated	Develops reasonable forecasts assuming 70%–75% of state DPV goals are met by 2023 following an S-shaped deployment curve. The 2016 forecast will introduce factors like payback and socioeconomics at the county level to develop forecast.	
PAC 2015 IRP	Customer-adoption modeling	Uses Navigant-developed forecast based on relationship between simple payback and willingness-to-adopt curve (described below). The annual adoption rate is determined by the Fisher-Pry model.	
PG&E 2014 BPP [Alternate]	Historical trend	Assumes a 29% growth rate for 2014–2016 based on historical trends. Owing to assumed expiration of the ITC, the 2017 adoption rate returns to the 2014 level of approximately 300 MW/year and thereafter increase linearly to about 400 MW/year by 2024.	
PG&E 2014 BPP [California Public Utilities Commission (CPUC) Mandated]	Customer-adoption modeling	Uses customer-adoption model forecast from the California Energy Commission (CEC) based on the relationship between payback and willingness-to-adopt curve. The annual adoption rate is determined by the Bass diffusion model. The CEC forecast for non-residential customers is based on historical trends.	
PJM 2015 Forecast Manual	Other	Uses a proprietary (not provided) state-by-state DPV adoption forecast from IHS Energy.	
PNM 2014 IRP	Stipulated	Assumes capacity additions of 15 MW in 2014, 18 MW in 2015, and 21 MW thereafter.	
PSE 2015 IRP	Customer-adoption modeling	Uses customer-adoption model developed by Cadmus. Market penetration rate is estimated from regression of historical market penetration rate on annualized simple payback and then extrapolated based on estimates of future payback.	
TGT 2015 IRP	Stipulated	Assumes 20% of all residential customers, or 90,000 customers, would drop completely off the grid in a scenario where DPV + storage leads to grid defection.	
TEP 2014 IRP	Program-based and stipulated	Bases forecast on requirement that DG (90% of which is DPV) makes up 30% of the overall renewable resources used to meet a 15% Renewable Energy Standard by 2025. Also includes a what-if scenario in which only a portion of the DG requirement is met.	
TVA 2015 IRP	Other	Creates DPV forecasts under five scenarios based on correlating scenarios with EIA AEO scenarios based on carbon policy and assuming some fraction of the national renewable forecast is derived from rooftop PV.	
WECC 2015 Transmission	Customer-adoption modeling	Uses customer-adoption model developed by E3 based on relationship between payback and willingness-to-adopt curve. The annual adoption rate is determined to the Bass diffusion model. E3 creates a reference forecast that limits DPV adoption assuming existing NEM caps stay in place and a high-DG forecast assuming no NEM caps and lower DPV capital costs.	

3.2 Customer-Adoption Modeling

The customer-adoption modeling approach explicitly models consumer decision making based on PV economics. This approach is used in five of the planning studies reviewed, including those by PG&E (CPUC Mandated scenario, conducted by the CEC), NWPCC, PAC (conducted by Navigant), PSE (conducted by Cadmus), and WECC (conducted by E3). A key benefit of customer-adoption models is their ability to generate new, self-consistent DPV-adoption forecasts with varying assumptions about customer economics or policies. For example, Cadmus generates distinct high and low forecasts for PSE based on different assumptions about the renewal of DPV incentives. PAC uses customer-adoption modeling to create low-, base-, and high-penetration cases from various DPV-cost, DPV-performance, and utility-rate-escalation scenarios (Figure 2). This approach enables a bottom-up assessment of individual drivers instead of presupposing the impact that drivers might have on DPV deployment. On the other hand, projections of customer economics are still highly uncertain given potential changes in rates, policies, and DPV costs. Customer-adoption models provide a coherent framework for assessing the impact of these changes on DPV adoption, but they still produce uncertain forecasts.

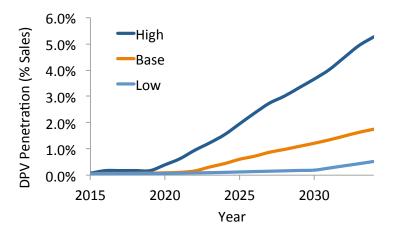


Figure 2. DPV Penetration Scenarios from PAC's Customer-Adoption Modeling

Four of the five aforementioned planning studies (all but NWPCC's, which is discussed at the end of this subsection) follow a similar underlying process in their customer-adoption modeling

¹³ Sacramento Municipal Utility District (SMUD) worked with Black & Veatch to develop a DPV forecast based on a customer-adoption model, similar to the models described here (Clark 2015, Wilson et al. 2015). We note interesting aspects of their analysis throughout this document, but we did not have a particular publicly available planning study to comprehensively include in our review. Relative to the other customer-adoption models, a clear innovation in the Black & Veatch approach is to add further granularity to where (i.e., on which distribution feeders) adoption is likely to occur. This is discussed further in Section 7.

¹⁴ It would also be possible to evaluate the effects of alternative rate designs (e.g., NEM alternatives, time-of-use rates, demand charges, or increased fixed charges) on the DPV forecast, but no utility investigated this. Previous research by Lawrence Berkeley National Laboratory (Darghouth et al. 2016) uses the National Renewable Energy Laboratory's (NREL's) SolarDS model to evaluate the impact of alternative rate designs on DPV adoption across the United States. Bringing rate-design decisions into utility planning studies is further discussed in Section 11.

(Figure 3). DPV deployment is estimated via three steps: (1) assessing the maximum capacity that could feasibly be installed, regardless of economics (technical potential); (2) assessing the ultimate potential DPV adoption based on the customer economics of PV (willingness-to-adopt), which is based, in turn, on a combination of technology costs, retail electricity rates, NEM, and other incentives; and (3) simulating deployment over time by combining the adoption curve with a theoretical adoption model (diffusion), where the Bass diffusion model and the Fisher-Pry model are two of the most popular options (see Text Box 1 below for a brief introduction). The basic approaches used by the utilities are similar to NREL's SolarDS (Denholm et al. 2009) and dGen models (Sigrin et al. 2016).

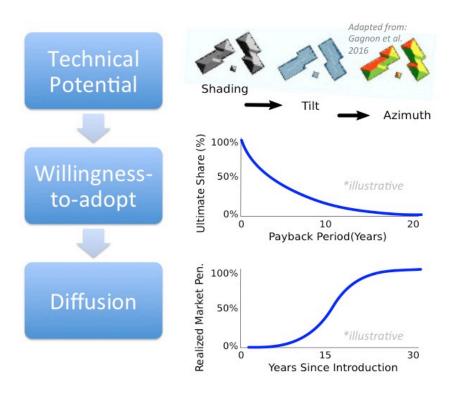
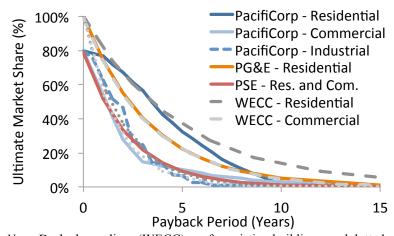


Figure 3. Illustration of Process Commonly Used to Develop Customer-Adoption Models

For three of the studies (PSE, PAC, and PG&E), the technical potential assessments are based on estimates of available rooftop space and customer counts. For PSE, the rooftop space is estimated based on average floor space, average number of floors, and the customer count for each customer type. PSE includes adjustments in available area based on factors like orientation, pitch, and fire codes, and it projects that the PV array power density would increase at a rate of 2.1% per year based on projected efficiency gains in PV systems (PSE 2015, Appendix M). PAC estimates technical potential based on the smaller of the customer's summer peak load or the available rooftop space. Rooftop space is estimated based on PAC's own floor-space surveys and assuming an average of two floors per building. The average rooftop space is then reduced based on an assumption that only one in four residential customers has a south-facing roof (a PV "access factor" of 25%), only a portion of commercial roof space is suitable (an access factor of 65%), and the power density of a system is only 80% of the density of a module owing to maintenance access, footpaths, etc. The technical potential for the CEC forecast used by PG&E is based on an approach similar to PAC's, using an earlier technical potential assessment for

California conducted by Navigant (Navigant 2007). The technical potential for WECC assumes that 50% of customers could add PV and that typical system sizes are 4 kW for residential and 50 kW for commercial customers (WECC 2015).

The willingness-to-adopt curve is a relationship between the customer economics of PV (often represented by the simple payback period) and the ultimate market share that could be achieved with enough time (as a percentage of the technical potential). The willingness-to-adopt curves used in the utility forecasts are shown in Figure 4. The willingness-to-adopt curves used by PAC were developed by Navigant through previous research based on customer surveys, historical program data, and industry interviews. The curve used by the CEC for PG&E's forecast is from a customer-adoption model (SolarSim) in an Arizona PV study by R.W. Beck (2009), which averages curves from Navigant and curves developed based on heat pump adoption (Kastovich et al. 1982). PSE references the same curve used by PG&E, though it ultimately develops its own curve, citing concern that PSE customers may have different preferences. The WECC curves have the same functional form found in NREL's SolarDS model. The simple payback period accounts for the cost of purchasing a PV system, the bill savings (which depend on PV performance and retail rates), and incentives.



Note: Dashed gray lines (WECC) are for existing buildings, and dotted gray lines are for new buildings.

Figure 4. Willingness-to-Adopt Curves Used in Utility Customer-Adoption Models

To develop an annual adoption rate, PAC, PG&E, and WECC use a diffusion curve to estimate the fraction of the ultimate market share that would be achieved in each year, depending on time since PV was introduced into the market (Figure 5). PAC uses the Fisher-Pry curve, while PG&E and WECC use the Bass diffusion curve, described below in Text Box 1. For the PG&E forecast,

¹⁵ PAC's payback period accounts for state-specific rebates and retail rates.

¹⁶ To develop the willingness-to-adopt curve, Cadmus Group estimated the payback period for historical years and the market share as a percentage of the technical potential from historical adoption. It then fit a curve to this historical data as the basis for the willingness-to-adopt curve. One limitation of this approach is that it ignores the diffusion component that is included in the PAC and PG&E forecasts. HECO used a similar fitting process in the customer-adoption forecast used in their 2016 PSIP.

the parameters that define the curve shape are derived from a survey of empirical studies.¹⁷ The source of the parameters is not clear for PAC¹⁸ and WECC. For PAC, the "Years Since Introduction" starts when the simple payback period is first less than 25 years. In contrast, PSE does not appear to use a diffusion curve—the realized market potential is the same as the ultimate market potential in each year.

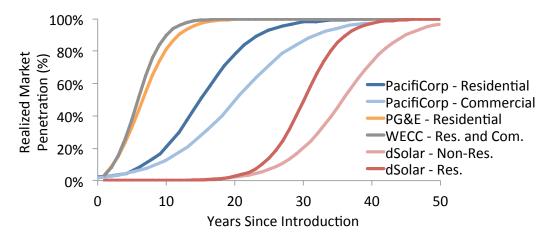


Figure 5. Diffusion Curves Used in Customer-Adoption Models

For comparison, NREL's dSolar model estimates Bass diffusion parameters for each state based on historical adoption rates (Sigrin et al. 2016, Appendix D). The number of years since technology introduction, key to these calculations, depends on the state-specific diffusion parameters as well as the current penetration rate. The median values across all states shown in Figure 5 imply market diffusion starting between 1998 and 2005. Advantages of this approach are that the Bass diffusion parameters reflect territory-specific trends and can be readily updated as more customers adopt DPV. The disadvantages are that year-to-year volatility in adoption can bias estimates, and the parameter estimates invariably embed some knowledge of prior historical techno-economic conditions, which may not reflect future conditions.

The S-shape of the diffusion curves in these forecasts is not unique to DPV. Historical adoption rates of many different kinds of technologies—including refrigerators, VCRs, internet access, and mobile phones—have been modeled with S-shaped curves (Meade and Islam 2006, Kemp and Volpi 2008). This pattern of adoption implies that market penetration in 5–10 years can be significant even if recently observed shares of adoption are small. However, there appears to be no clear agreement about the number of years between DPV introduction and the rapid growth phase. Limitations of these existing customer-adoption models are addressed in Section 3.5.

¹⁷ Specifically, the study uses a coefficient of innovation (p) value of 0.03 and a coefficient of imitation (q) value of 0.38 derived from a survey in Meade and Islam (2006).

¹⁸ Navigant discusses 12 factors that affect the parameters of the Fisher-Pry curve, including the payback period, the market risk, the technology risk, and the amount of government regulation. It does not, however, describe how these factors translate into the particular parameters it chose to model the diffusion curve. For residential customers, it appears Navigant uses a t_m of about 15 years and a Δt of about 16 years. For commercial customers, t_m is about 20 years, and Δt is about 23 years. Navigant does not explain the differences in the curve parameters.

Text Box 1. Two Diffusion Models

Many diffusion models in the literature can produce an S-type diffusion curve for new technology adoption. Two common choices are the Bass diffusion model and Fisher-Pry model. Borrowing Meade and Islam's (2006) language, while the Fisher-Pry model is purely an internal-influence model, the Bass diffusion model is a mixed-influence model: a mix of both internal and external influence. Internal influence represents interpersonal communication and the phenomenon of later adopters imitating early adopters; on the other hand, external influence represents the impact of innovators that adopt the new technology without others' suggestions.

In mathematical terms, these two diffusion models can be specified in a similar form:

Fisher-Pry:
$$\frac{f_t}{(1-F_t)} = \alpha \cdot F_t \tag{1}$$

Fisher-Pry:
$$\frac{f_t}{(1-F_t)} = \alpha \cdot F_t \tag{1}$$
Bass diffusion model:
$$\frac{f_t}{(1-F_t)} = p + q \cdot F_t \tag{2}$$

Where, f_t is annual adoption rate in year t, F_t is the cumulative adoption rate in year t, and $\frac{f_t}{(1-F_t)}$ is the odds ratio of adoption rate. In the Fisher-Pry model, α is half the annual fractional growth in the early years. In the Bass diffusion model, p is the coefficient of innovation, and q is the coefficient of imitation.

Comparison of the models makes it clear that the Fisher-Pry model relies only on the internal influence that is captured by the amount of cumulative adopters (F_t) , whereas the Bass diffusion model allows for external influence based on the coefficient of innovation (p).

The Fisher-Pry model can be solved for the cumulative adoption rate, F_t , as follows:

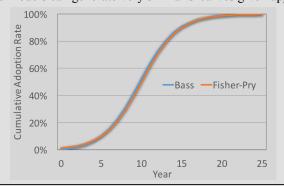
$$F_t = \frac{1}{1 + exp\left(-\frac{\ln{(81)}}{\Delta t}(t - t_m)\right)} \tag{3}$$

Where t_m is the time to fulfill 50% of the cumulative adoption rate (i.e., the middle point), and Δt is the time it takes for the adoption rate to increase from 10% to 90%.

In the solution of the Bass diffusion model, F_t depends on the p and q parameters:

$$F_{t} = \frac{1 - exp(-(p+q)t)}{1 + \frac{q}{n}exp(-(p+q)t)} \tag{4}$$

As an illustration, these two models can generate very similar S-curves given appropriate parameterization.



Bass diffusion Model: p = 0.0063

q = 0.4282

Fisher-Pry Model: $\Delta t = 10$

 $t_{m} = 10$

NWPCC's customer-adoption modeling approach is slightly different than that used in the other four studies. Primarily, NWPCC includes in its load forecast adoption of DPV as a choice between purchasing electricity from the grid versus purchasing electricity from DPV. Specifically, the demand model used by NWPCC (based on the Energy2020 model from

Systematic Solutions, Inc.) uses a multinomial logistic model to predict consumer decisions when faced with competing alternatives, in this case the choice between purchasing grid electricity at retail rates or installing behind-the-meter PV. Historical DPV adoption rates, along with data for electricity rates and DPV cost and performance, are used to calibrate the model to account for economic and non-economic factors. No explicit diffusion curve is used in the model, though the multinomial logistic model can produce a forecast that follows an S-shaped curve. The forecast is developed from the model by projecting future retail electricity prices and PV cost and performance. Variations in the retail electricity prices and PV system costs produce different DPV forecasts. NWPCC assumes DPV costs will fall at the same rate as they project for utility-scale PV (UPV), but performance (as measured by the state-specific capacity factor) will remain the same as today.

3.3 DPV Deployment Drivers

When developing DPV forecasts, utility planners may consider various drivers of future DPV deployment. The relationship to the DPV forecast may be explicit, as with customer-adoption modeling, or it can be more implicit, for example, by informing planners' judgment when stipulating DPV growth under a "what-if scenario" approach. We group the drivers of DPV deployment considered by utility planners into four categories below.

- DPV economics: The customer economics of PV directly impact deployment and can be influenced by many factors, such as DPV technology cost and performance, federal and state incentives (e.g., an ITC), new business models (e.g., third-party ownership), electricity prices, and rate design (including the availability of NEM). For all planning studies that use customer-adoption modeling, DPV economics is a necessary consideration, because DPV deployment is forecasted based on payback periods. To calculate payback, annual cash flow is required to account for benefits and costs, and various DPV economics factors can play an important role. DPV economics is the most common driver of DPV forecasts across the various planning studies.
- Public policy: Other forms of public policy support, beyond direct incentives, can also impact DPV economics. Common examples include state RPS requirements and environmental policies such as CO₂ regulation. HECO, for example, considers the overall level of public policy support for clean energy as one of the two dimensions (the other being the price of oil) to create four broad scenarios in its IRP. Similarly, ELA includes a "Distributed Disruption" scenario that assumes broad state support for DG. APS expects higher rates of DPV adoption in its "Increased Environmental Policy Scenario," because it assumes environmental policies will increase demand for renewables and thus increase retail rates and the economic attractiveness of DPV.
- Customer preferences: DPV deployment projections may also be shaped by customer preference for DPV technology or, more generally, increased customer choice. Three planning studies highlight the importance of customer preferences. DEI includes an upper-bound forecast in a stakeholder-inspired "Increased Customer Choice" scenario. NSP makes customer participation in a new community solar program its main source of uncertainty. TVA has various scenario-specific assumptions that vary based on how much customers are assumed to prefer DG.

• *Macro factors:* DPV deployment may also be driven by factors at the macro level, such as economic growth, load growth, oil and gas prices, and the cost and availability of complementary technologies, such as batteries. One example is a TGT scenario that envisions significant grid defection from customers going off-grid with DPV and battery systems. The impact of such factors is less direct than the impact of other factors.

3.4 DPV Forecasted Quantities

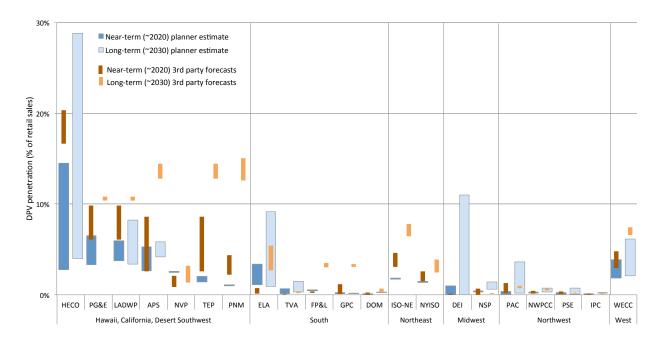
As expected, the quantity of forecasted DPV varies substantially by region and utility. Figure 6 compares the ranges of DPV forecasts across plans, expressed as a percentage of retail sales, in the near-term (2020) and long-term (2030); Appendix B provides additional details. These forecasts provide context about the applicability of the planning strategies discussed in this report to different regions and utilities, as perceived by planners. Fewer than half of utilities consider DPV penetration levels beyond 1% of sales by 2020, even at the high end of their range—and these low forecasts span areas with high insolation (e.g., the South) and low insolation (e.g., the Northwest). As a point of reference, EIA's forecast of the national average DPV penetration is 0.5%–1% of retail sales by 2020 and 0.8%–2% by 2030. 19

A number of utilities use only a single DPV forecast or consider only a small range, which might indicate opportunities for these utilities to expand the scope of their forecasting approaches. For example, though NVP and PNM forecast substantial near-term deployment, the ranges of those forecasts are small compared with the forecasts produced by other organizations in their region and compared with industry forecasts. ISO-NE and NYISO also have very small ranges, which result from the focus of these regional planning organizations on a central case. Numerous utilities with low forecasts also have small forecast ranges, but these often accord with the ranges of other utilities in their regions.

Figure 6 also shows that the high end of third-party forecasts is above the high end of planning forecasts about two thirds of the time, suggesting that differences between these two types of analyst groups might result in relatively conservative estimates from utility planners. Some differences might be due to different forecast vintages, because most utility forecasts were developed before the recent ITC extension. Differences could also stem from different forecasting approaches. For example, the long-term APS forecast is primarily driven by RPS requirements for DG, whereas the much higher NREL dSolar forecast is driven by customer economics. Similarly, GPC's low long-term forecast is primarily based on a program goal, which makes it lower than the high end of the near-term third-party forecasts and lower than the full range of the dSolar 2030 forecast. In addition, utilities might make more conservative forecasts, because the risks associated with forecasting too little DPV (which can lead to extra costs from overbuilding the system) are less acute than the risks of forecasting too much (which can lead to reliability issues if insufficient resources are available). In any case, this comparison suggests

¹⁹ The range is based on the Reference case from the 2015 AEO, which assumes the ITC would sunset after 2016 and the Clean Power Plan would not be enacted, and the Reference case from the 2016 AEO, which includes the recent ITC extension and the Clean Power Plan.

that third-party forecasts could provide additional useful context for utility planners, particularly when considering plausible high-end forecast values.

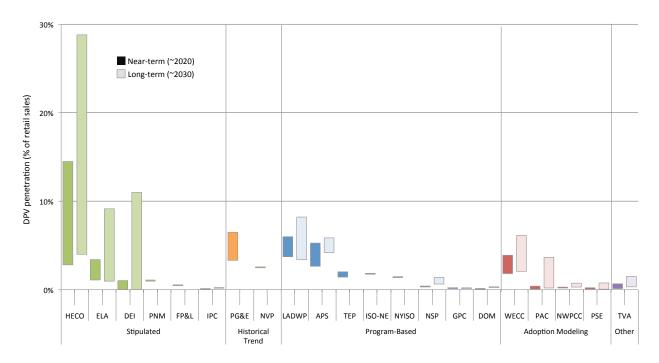


Note: All utility planner estimates are for the year 2020 (dark blue) and 2030 (light blue, if a forecast was made) with the exception of APS, whose long-term estimate is for 2029. Third-party forecasts of DPV adoption include BNEF (2015), GTM Research and SEIA (2015, 2016), and NREL's dSolar forecast (Gagnon and Sigrin 2016). Bloomberg New Energy Finance (BNEF)²⁰ and dSolar use a customer-adoption model to generate forecasts. The only third-party forecasts for 2030 are from NREL's dSolar. NREL's dSolar forecasts include a range of scenarios with varying DPV and carbon costs.

Figure 6. Utility DPV Forecasts in the Near Term (2020) and Long Term (2030) Compared with Third-Party DPV Forecasts

Overall, our analysis suggests that combining various DPV forecasting approaches might be valuable. Figure 7 separates the forecasts by forecasting approach. It shows that stipulated forecasts generally have the largest ranges, whereas program-based forecasts tend to have small ranges (with the exception of LADWP, which considers various program portfolios, and APS, which stipulated adoption higher than the program goal in one scenario), typically focused on the near term. A combined approach might, for example, use program goals discounted for uncertainty as lower bounds, customer-adoption models to forecast expected levels, and third-party forecasts and stipulated what-if scenarios to explore the full range of plausible futures.

²⁰ BNEF uses a Norton-Bass model that allows for customer choices among several product options (e.g. DPV in combination with storage) and calibrates customer-adoption parameters with historical monthly installation data. Their model has the resolution of a utility service territory, accounts for regional DPV system price variations, and utilizes utility-specific incentives and energy tariffs.



Note: All utility planner estimates for the near term (2020) are shown in darker colors. Longer-term estimates are depicted in lighter colors and pertain to the year 2030 with the exception of APS, whose long-term estimate references the year 2029. As noted in Table 5, some forecasts use multiple methodologies. In such cases, we used our judgment to categorize the forecast's methodology.

Figure 7. Utility DPV Forecasts Grouped by Forecasting Methodology

3.5 Advancing Customer-Adoption Models

As discussed in Section 3.2, currently used customer-adoption models do not clearly agree on all parameters, methods for developing parameters are not always clear, and the models do not always exploit the larger amounts of data available as more customers adopt DPV. As DPV deployment has increased, the sophistication of methods used to analyze customer preferences and predict PV adoption has also improved. Roughly speaking, these methods predict aggregate deployment in a top-down (using regional-level characteristics) or bottom-up (using individual-level characteristics) manner. In this subsection, we highlight recent state-of-the-art models that have been used to forecast DPV adoption, and we note unresolved issues in the literature. Though these advanced methods are not employed in the utility planning documents we review, they build on the customer-adoption modeling framework described in Section 3.2 and represent potential improvements to DPV forecasting tools.

3.5.1 Improving Representation of Customer-Adoption Decisions

Agent-based models (ABMs) have emerged as common, bottom-up techniques for simulating customer adoption of new technologies, because they are well suited to represent the complexities of consumer behavior and technology valuation. ABMs are a class of computational models for simulating the interactions and actions of distinct autonomous agents and, by association, assessing their effects on a larger system. These models have been successfully used to forecast aggregate PV deployment at the city, regional (Rai and Robinson

2015, Zhang et al. 2015), and national levels (Sigrin et al. 2016). An overarching feature of ABMs is the parameterization of the factors that influence decision making by agents representing individuals or groups of consumers—and the heterogeneity of the population therein, as well as regional descriptors. This class of models is well suited to producing geospatial forecasts.

At the core of all bottom-up models, ABM or otherwise, is some defined relationship between the adoption decision and the variables that affect this decision. Two ongoing questions in this field are how to quantify the elasticity of demand to DPV profitability (Gillingham and Tsvetanov 2016) and how to quantify the importance of non-economic factors, such as socioeconomic status or environmental concern. Agarwal et al. (2015) define the probability of adoption as a function of bill savings and existing penetration levels. This model, which was trained on prior adoption history for southern California, finds that demographic factors are a second-order effect compared with system profitability. In contrast, Zhang et al. (2015) use machine-learning techniques to develop building-level adoption probabilities.

Top-down models are generally statistical in nature, regressing adoption rates on regional summary statistics. Davidson et al. (2014) use several types of geospatial information—including population demographics and housing characteristics—in a stepwise regression model to identify which subsets of geospatial information best predict historical PV adoption at the zip code level. Discrete choice models, as used in NWPCC's customer-adoption model described earlier, are also popular for modeling technology diffusion (Higgins et al. 2014, Jun and Kim 2011, Lobel and Perakis 2011, Kim et al. 2005) owing to their ability to model competition between several options; this class of models also has a well-defined methodology for soliciting customer preferences. A subset of top-down models are probit models (Geroski 2000), regression models with binary dependent variables, and threshold models (Kemp and Volpi 2008), in which adoption decisions are explicitly modeled though a statistical representation of population variance. An example of an empirically derived forecast for German PV adoption using a form of discrete choice model called a *logit* model is shown in Figure 8 (Lobel and Perakis 2011).

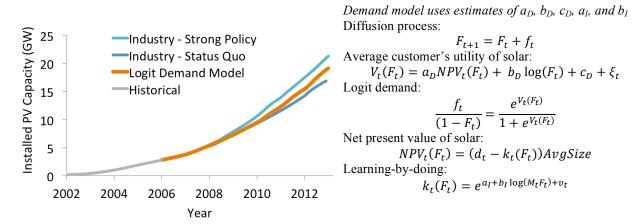


Figure 8. Example of PV Forecast Using Logit Demand Model Fit to Empirical Data from Germany (adapted from Lobel and Perakis 2011)

Quantifying the influence of social networks on probability of adoption is another important line of research (Bollinger and Gillingham 2012, Graziano and Gillingham 2015). Related are

"network externalities" that promote competition and accelerate learning, potentially yielding lower prices and increasing adoption (Lobel and Perakis 2011). One consistent finding in this field is the importance of "peer effects"—individuals are more likely to consider adopting when they are socially or physically proximate to systems adopted by their peers.

Though the PV-diffusion literature is actively growing, a number of questions are unresolved. These include, but are not limited to, understanding how gross consumption of customers changes after PV adoption (i.e., the "rebound" vs "ripple" effect), how customer demand varies with PV profitability and across market segments, and how to determine demand for emerging business models such as community solar or aggregated NEM. While no single approach reviewed is definitively superior to the others, commonalities among many of the approaches highlight the key features in advanced PV adoption models. These include reflecting the heterogeneity of potential consumers, representing regional or locational differences, grounding methods in empirical data, and including non-economic factors.

3.5.2 Improving Representation of Innovative Business Models

Innovative DPV business models, such as third-party ownership, or emerging ones, such as community solar or aggregated NEM, constituted roughly 60% of installed residential capacity in 2015. A growing body of behavioral science research (e.g., Frederick et al. 2002, Rai and Sigrin 2013) explains customer preferences for leasing or other low-money-down financing options by assuming consumers use high discount rates—higher than the opportunity costs of capital—to evaluate energy technology investments. A major appeal of leasing for consumers is ready access to financing, often with no down payment required.

Some representation of leasing is therefore important, though it can be challenging to empirically represent in customer-adoption models. Recent research indicates that most consumers now use monthly bill savings to evaluate potential DPV investments (Sigrin et al. 2015, Dong and Sigrin 2016). Thus one approach, used in NREL's dSolar model, is to represent the financial appeal of leasing through a monthly bill savings metric as opposed to payback period in the willingness-to-adopt curve described earlier (see Figure 9). Payback period is undefined for zero-down financing. Dong and Sigrin (2016) estimate willingness-to-adopt for the bill savings metric using elicited survey data that are further calibrated against historical relationships between bill savings and customer adoption.

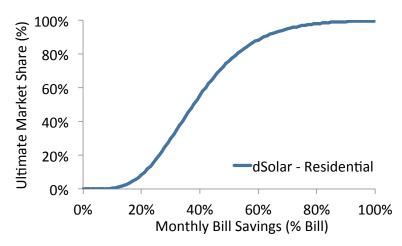


Figure 9. Willingness-to-Adopt Curve Suitable to Leasing Options Used in NREL's dSolar

Additional constraints that can be considered in models are the fraction of households that have sufficient savings for cash purchases and how household creditworthiness (e.g., FICO scores) would limit access to financing.

3.5.3 Improving Estimates of Rooftop Technical Potential

Technical potential for DPV refers to either the feasible number of buildings on which DPV could be installed or the feasible amount of DPV generation capacity that could be installed, regardless of economic considerations. Because the vast majority of DPV has been sited on rooftops, current estimates of DPV technical potential are essentially synonymous with available rooftop space for a region's building stock. Rooftop space can be estimated via top-down or bottom-up methods. Top-down estimates are based on territory-wide statistics, such as the number of buildings in the area, which are derated by assumptions about the available rooftop area per building, the percentage of buildings with usable roofs, and so on (e.g., Denholm and Margolis 2008). Bottom-up estimates are typically based on Light Detection And Ranging (LiDAR) imagery to identify suitable solar roof areas for a representative sample of actual buildings in the region, where shading, tilt, and azimuth attributes can be inferred from the rooftop images (Gagnon et al. 2016). For each rooftop imaged, availability constraints can be applied to exclude unsuitable rooftop orientations or insufficiently large contiguous areas. Where feasible, technical potential estimates can also exclude building stock based on permitting and zoning considerations. Such technical potential estimates need to be updated over time to reflect building block growth, tree growth/removal, and PV efficiency improvements.

4. Ensuring Robustness of Decisions to Uncertainty in DPV Quantity

Planner's question: How do you make sure your planning decisions make sense even if there is uncertainty in how much DPV will be adopted in the future?

In general, utilities aim to develop plans that are least cost while meeting specific criteria. One challenge to these efforts is the uncertainty of future conditions. Some planners simply identify a least-cost plan under expected conditions, without directly addressing uncertainty. Others try to address uncertainty by identifying plans that are either robust to changes in conditions or flexible enough to adapt to changing conditions.

Customer adoption of DPV and growth of DPV through utility programs represent additional sources of uncertainty. Different amounts of DPV can change the amount of capacity and energy that must be met by other utility resources as well as the temporal profile of those needs (i.e., the shape of net load). Robustness of decisions to uncertain parameters is most clearly addressed in utility integrated resource planning, though we also find relevant examples in transmission planning. We find little evidence that robustness of decisions to DPV forecast uncertainty is a consideration in distribution planning, likely owing to a combination of factors. First, distribution system planning horizons are shorter than those for resource or transmission planning, so DPV quantity forecasts are more certain. Second, planners are less confident that DPV can defer distribution system upgrades due to higher variability and less coincidence with peak feeder loads, particularly on residential feeders, which lessens the importance of getting the DPV quantity right in the plans. These factors are discussed further in Section 8.

In this section, we address methods that utilities use to ensure decisions are robust to uncertainty in DPV forecasts. Section 4.1 gives an overview of the methods used, highlighting examples from various U.S. utilities. Section 4.2 provides additional detail on the per-scenario-plan method as well as an innovative variation of that method: acquisition path analysis.

Innovative Uncertainty Planning: Acquisition Path Analysis

Innovations in uncertainty planning revolve around the ability of analytical methods to capture multiple sources of uncertainty and inform resource decisions. In this regard, the methods discussed in this section provide a spectrum of options for capturing uncertainty related to DPV quantity, as summarized in Table 6. Acquisition path analysis, which combines multiple per-scenario plans with trigger events to shape resource-acquisition strategy, is among the most innovative approaches currently employed by utility planners. PAC and HECO use variations of this approach in their resource planning, as described in Section 4.2.

Table 6. Factors Addressed by Various Methods for Addressing Uncertainty of DPV Quantity

Method	Description Factors Addressed				
		Net load changes	Generation portfolio changes	Resource-acquisition strategy changes	
Single Forecast	One DPV-adoption forecast used				
Subject to Sensitivity	Cost and performance of portfolios evaluated under different sensitivities	X			
Per-Scenario Plan	CEM used to develop least-cost plans for various scenarios	X	X		
Acquisition Path Analysis	Multiple per-scenario plans combined with trigger events to shape resource-acquisition strategy	X	X	X	

4.1 Methods for Integrating Uncertainty of DPV Quantity into Planning

Across the utility studies in our sample, we observe wide variation in the approaches for ensuring robustness of decisions to different levels of DPV adoption. For all utilities, DPV uncertainty is just one of the many uncertainties faced when developing a plan, and approaches to addressing it are shaped by each utility's overall approach to managing uncertainty. We observe three basic methods for managing uncertainty in DPV adoption, which we describe below along with examples of real-world use. Table 7 compiles the methods used across the plans we reviewed.

Single forecast: Only one forecast of DPV adoption is used, and the utility plans are based on this level of DPV adoption. ²² DEC/DEP, FPL, GPC, NVP, and PNM use this method. With only

²¹ Related to this, alternative DPV forecasts are sometimes evaluated as an isolated factor that may change independently of other sources of uncertainty. At other times, alternative DPV forecasts are evaluated as one of multiple changes in an alternative scenario (e.g., as part of an increased environmental policy scenario that includes greater DPV adoption, a higher carbon price, and lower load growth). The approach for dealing with alternative

DPV forecasts is usually driven by the utility's overall approach to managing uncertainty.

²² Even if a single forecast of the quantity is used, utilities often consider various output levels of DPV in studies depending on the time of day or season. See Sections 6 and 8 for more details.

a single forecast, the utility cannot determine the impact that higher or lower levels of DPV adoption will have on the performance of its recommended plan. This makes it difficult to know if and when recommended decisions should change if DPV adoption is different than the expected level.

Subject to sensitivity: The cost and performance of portfolios are evaluated under different sensitivities, including a DPV-adoption sensitivity. DOM and DEI use this method. DOM shows that the present value of the revenue requirement (PVRR) of portfolios changes with higher DPV adoption, and DEI shows how the ranking of portfolios, based on PVRR, changes with higher DPV adoption. However, because the sensitivities change the net load but not the planned resources, the only impact to the PVRR is the change in fuel and purchased power costs. This approach can show the relative performance of different portfolios under varying conditions, but, because the candidate portfolios are fixed, it does not show how the timing or composition of resources in a portfolio might change. We cannot ascertain how these sensitivities are used to inform selection of the final preferred plan; at best, they show that there are no particular shortcomings of the preferred plan across the sensitivities.

Per-scenario plan: A capacity-expansion model (CEM) or similar tool is used to develop a least-cost plan for each of various scenarios, including scenarios with greater adoption of DPV. Many utilities (APS, ELA, HECO, NSP, NWPCC, PAC, PG&E, PSE, TGT, TEP, and TVA) use this method, which is illustrated in Figure 10. For some of the planning studies, the utility reports a reduction or deferral of conventional capacity in the least-cost plan for scenarios with higher DPV adoption (e.g., APS, ELA, TEP, and TVA) and/or a reduction in the capacity of other renewable generation (e.g., HECO and TVA).

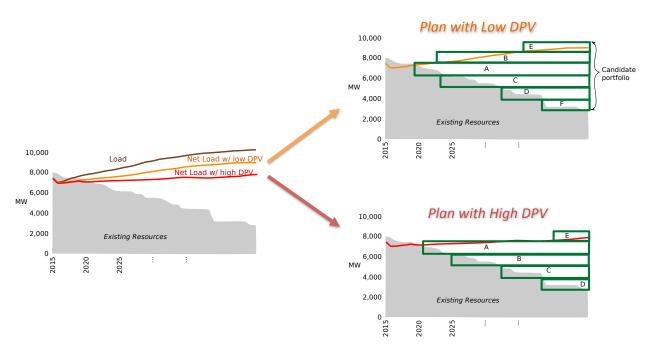


Figure 10. Illustration of Process for Developing Per-Scenario Plans

Table 7. Methods for Addressing DPV-Adoption Uncertainty across Reviewed Plans

Plan	Method	Details
APS 2014 IRP	Per- Scenario Plan	Use CEM (Strategist) to develop plans in six scenarios, several with different DPV assumptions. Use to show how plans might change if/when conditions change.
DOM 2015 IRP	Subject to Sensitivity	Use CEM (Strategist) to develop plans in five scenarios, then subject each plan to sensitivities including DPV growth.
DEC/DEP 2014 IRP	Single Forecast	Use CEM (System Optimizer) to develop plans based on a single DPV forecast.
DEI 2015 IRP	Subject to Sensitivity	Use CEM (System Optimizer) and stakeholder input to develop nine different candidate portfolios, then subject each to seven different scenarios including one with higher DPV adoption. Rank each portfolio by lowest cost (lowest PVRR) in each scenario.
ELA 2015 IRP	Per- Scenario Plan	Use CEM (Aurora) to develop plans in multiple scenarios, including one "Distributed Disruption" scenario. Evaluate each plan under assumptions from different scenarios and various sensitivities to show that recommended plan is sufficiently robust.
FPL 2015 10- Year Plan	Single Forecast	Develop plan based on a single DPV forecast.
GPC 2016 IRP	Single Forecast	Use CEM (System Optimizer) to develop plans based on a single DPV forecast.
HECO 2013 IRP	Per- Scenario Plan	Use CEM (Strategist) to develop plans in four scenarios, each with different DPV assumptions, along with other plans under sensitivities within each scenario. Develop flexible plan that can be robust to uncertain futures. Monitor conditions to drive timing of decisions like building new power plants or retiring old plants.
NVP 2015 IRP	Single Forecast	Develop candidate portfolios based on a single DPV forecast.
NSP Resource Plan 2015	Per- Scenario Plan	Use CEM (Strategist) to develop plans in 12 scenarios that have either a low or high quantity of DPV. Rank each plan by lowest PVRR and lowest present value of social cost (which includes a ~\$22/ton of CO ₂ cost of carbon).
NWPCC 7 th Power Plan 2015	Per- Scenario Plan	Use CEM (Resource Planning Model, developed by NWPCC) to develop plans in many different scenarios, including a range of potential DPV adoption rates.
PAC 2015 IRP	Per- Scenario Plan	Use CEM (System Optimizer) to develop plans in many different scenarios, including sensitivities with high and low DPV. The resource plan in the sensitivity is benchmarked to a core case to show the change in timing of thermal resource acquisition. An acquisition path analysis identifies trigger events, including higher or lower sustained DPV penetration levels that will alter the resource acquisition strategy.

PG&E 2014 BPP	Per- Scenario Plan	Identify procurement needs in scenario using CPUC-mandated assumptions and in scenario with PG&E's higher DPV-adoption assumptions.
PNM 2014 IRP	Single Forecast	Use CEM (Strategist) to develop plans based on a single DPV forecast.
PSE 2015 IRP	Per- Scenario Plan	Use internal model to build portfolios for different cases including a base case and a high-DPV case. Portfolio does not change, in part owing to assumption that DPV has no capacity credit in the winter-peaking utility.
TGT 2015 IRP	Per- Scenario Plan	Use CEM (System Optimizer) to develop plans in nine scenarios, including one that assumes a large number of customers go off-grid with DPV and storage. Compare resource plan in reference scenario to plans under other scenarios to show robustness of plan.
TEP 2014 IRP	Per- Scenario Plan	Use CEM (Aurora) to develop plans in multiple scenarios, including one with lower realization of EE and DG. Compare the resource plan in the reference scenario to plans under other scenarios to show robustness of plan.
TVA 2015 IRP	Per- Scenario Plan	Use CEM (System Optimizer) to develop plans in five scenarios, several with different DPV assumptions, using five different resource strategies. Compare the resource plan in the reference scenario to plans under other scenarios to show plan robustness.

4.2 Using Multiple Per-Scenario Plans and Acquisition Path Analysis

The studies that develop plans for each scenario differ in how they use the multiple plans to develop a recommended plan or action plan. The decision is easy when planners find that the plan does not change in the higher-DPV scenario. For example, winter-peaking PSE finds that the least-cost portfolio is the same in the reference case and the higher-DPV case, in part owing to its assumption that the capacity credit of DPV is zero. In Hawaii, HECO shows that the new transmission investments are the same irrespective of the DPV forecast on some islands, though transmission needs depend on the DPV scenario on other islands.

Multiple plans can also be analyzed by comparing the composition and timing of investments to indicate how the plans might change when the rate of DPV adoption changes from the expected. APS and TEP use this approach, as does HECO for transmission needs that vary depending on the amount of DPV. Though such comparisons demonstrate the sensitivity of plans to DPV forecasts, comparing plans alone does not inform the selection of the preferred plan or action plan.

ELA takes the analysis a step further by subjecting each plan, which is least cost under the conditions of a particular scenario, to assumptions from the other scenarios and sensitivities. It uses this detailed evaluation of each plan under varying outcomes to suggest that the recommended plan is sufficiently robust to uncertainties.

Finally, some utilities use the difference in plans across multiple per-scenario plans to develop a plan that is flexible enough to adapt to changing conditions. For example, PAC uses the System

Optimizer CEM to produce unique resource portfolios across a range of different planning assumptions. PAC builds resource portfolios for low and high DG penetration sensitivities, which are benchmarked to the core case. With low DG, the timing of the first deferrable thermal resource is unchanged relative to the benchmark case, but the total new thermal resource capacity increases by 212 MW by the end of the study period. With high DG, the first deferrable thermal resource is delayed by 3 years, and the total thermal capacity decreases by 423 MW by the end of the study period. PAC uses the different plans from each scenario to create an acquisition path analysis, establishing trigger events that include higher or lower sustained DG-adoption levels (Table 8). If these trigger events occur, PAC will change its near-term and long-term resource-acquisition strategy.

Table 8. PAC Acquisition Path Analysis Associated with DG Adoption

Trigger Event	Planning Scenario	Resource-Acquisition Strategy			
		Near-Term (2015–24)	Long-Term (2025–34)		
Higher sustained DG penetration levels	More aggressive technology cost reductions, improved technology performance, and higher electricity retail rates	 Reduce forward contract acquisition Continue to pursue EE 	 Reduce acquisition of gas- fired resources Balance timing of thermal acquisition with forward contracts and EE 		
Lower sustained DG penetration levels	Less aggressive technology cost reductions, reduced technology performance, and lower retail electricity rates	 Increase forward contract acquisition (primarily beginning 2024) Continue to pursue EE 	 Increase acquisition of gas-fired resources Balance timing of thermal acquisition with forward contracts and EE 		

Similarly, HECO uses its range of resource plans to identify a flexible action plan that is meant to be adjusted in response to future conditions. HECO uses the Strategist CEM to develop least-cost plans under each of four scenarios (each with different levels of DPV adoption) along with additional plans based on sensitivities within each scenario. The sensitivities explore impacts of decisions such as early retirement of generation or increases in demand response. HECO then picks four plans within each scenario to develop an action plan under each scenario. In contrast to its previous IRPs, HECO does not develop a single recommended plan. Instead, it identifies a flexible plan that can be robust to uncertain future circumstances, and it implements this plan by monitoring key parameters, such as DPV adoption rates, to drive the timing of decisions like adding new power plants or deactivating older units.

5. Characterizing DPV as a Resource Option

Planner's question: How do you evaluate the potential for DPV to be proactively deployed as a resource to meet projected needs?

In addition to changes in needs due to market-driven DPV, planners can invest in or incentivize DPV to meet needs. ²³ That said, fewer than half of the studies we review evaluate DPV as a resource that could be proactively deployed to meet future needs. Some planning studies that do not evaluate DPV as a resource cite the higher cost of DPV relative to UPV as justification. FPL, for example, indicates that the higher capital and maintenance costs of DPV make it twice as expensive as UPV. Studies that do consider DPV as a resource use various approaches to determine if it should be part of the plan and various ways to distinguish DPV from other resource options, particularly UPV.

This section discusses characterization of DPV as a resource option in resource planning studies (Section 5.1) and T&D planning (Section 5.2). It also addresses methods for distinguishing DPV from other resource options (Section 5.3) and determining DPV's cost effectiveness (Section 5.4).

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²³ DPV as a resource can include in-front-of and behind-the-meter PV. Some utilities consider programs to incentivize customers to adopt behind-the-meter DPV, while others consider utility investments in DPV, potentially on customer premises. Distributed community solar projects can also be considered as a resource, as in the case of NSP. Often, however, utilities do not specify the exact DPV business model.

Innovations in Distinguishing DPV from Other Resource Options

Some utilities dismiss DPV based only on its higher cost and lower capacity factor relative to UPV. However, DPV's capacity credit as well as the avoided losses, transmission deferrals, and distribution-system cost impact associated with DPV also can be important. Section 5.3 describes the characteristics considered by various utilities, and Table 9 shows which utilities use them. PG&E includes the most factors, which are also important for the locational net benefits methodology in the California DRPs (see Sections 5.1. and 5.2). In addition, customers who install DPV may receive non-monetary benefits, which an even more comprehensive cost-effectiveness assessment would address.

Table 9. Characteristics Used to Distinguish DPV from UPV or Other Resource Options

Plan*	Characterist	c				
	Capital Cost of DPV vs. UPV	Capacity Factor of DPV vs. UPV	Capacity Credit of DPV vs. UPV	Avoided Losses	Transmission Deferral	Distribution Deferral
DEI (2015)	X					
GPC (2016)				X	X	
HECO (2013)	X	X				
IPC (2015)			X			
LADWP (2014)	X				X	
NWPCC (2016)	X	X	X	X		
NSP (2015)	X	X	X	X		
PG&E (2014)	X	X	X	X	X	X
PSE (2015)	X				X	
TVA (2015)	X					

^{*}Plan references are in Appendix A.

5.1 Characterizing DPV as a Resource Option in Resource Planning Studies

Two methods for considering DPV as a resource in resource planning studies are most commonly used, with a number of less common variations. We describe these below, and Table 10 compiles the methods used across the plans we reviewed.

Candidate portfolio: Planners develop candidate portfolios with varying quantities of DPV and then examine the performance of each portfolio in terms of the PVRR and, in some cases, the volatility of the PVRR as key assumptions are varied (e.g., load growth rate, future fuel prices, and future carbon regulations). The planner or stakeholders in a planning study choose the quantity of DPV to be included in each portfolio and any corresponding adjustments to other portfolio resources. A comparison of the performance of each candidate portfolio then helps guide the planner's decisions regarding the preferred plan.

This approach is used by DEI, IPC, LADWP, and NSP. The DEI and IPC candidate portfolios with higher shares of DPV are stakeholder driven. In both cases, the high DPV portfolio is more expensive than other portfolios, so the higher DPV is not included in the preferred plan. LADWP and NSP, on the other hand, include higher DPV in their preferred plans. LADWP evaluates

different levels of DPV in response to a FiT program and the NEM program in various candidate portfolios. NSP increases the amount of participation in various solar programs, including the community solar program, in the Preferred Plan relative to the Reference Plan. Both utilities focus on cost minimization along with environmental requirements and strategic flexibility as part of their decision-making process.

CEM: A number of utilities use CEMs to develop candidate portfolios, and some include DPV as a resource option that can be selected in the model. In contrast to the previous approach, the quantity of DPV and the composition of the rest of the portfolio are both chosen by the model to minimize cost (typically the PVRR) including the cost of DPV.

This approach is used by HECO, NWPCC, TVA, and PSE. HECO and NWPCC include residential and commercial DPV systems as resource options in the Strategist CEM and Resource Planning Model, respectively. TVA includes small and large commercial DPV systems as resources in the System Optimizer CEM. PSE, in contrast, bundles DPV as a resource option along with other demand-side management (DSM) options with a similar levelized cost of electricity. PSE develops several different DSM bundles that can then be chosen as resources in the PSM III model (an internal model developed by PSE). Across all four of these examples, DPV is never selected by the model to be part of the least-cost portfolio that meets utility needs. UPV, however, is selected in some scenarios for these same four planning studies.

Other: Some planning studies use other, somewhat unique approaches to evaluate DPV as a resource.

- RPS Calculator in PG&E's BPP: The RPS Calculator, developed by E3 and the CPUC, is used to plan resources to meet the RPS requirements net of existing commitments (the "net-short"). Each renewable resource option, including DPV, is scored based on four metrics: permitting time, net cost, environmental impact, and commercial interest. A weighted average of the four scores is then used to identify the most attractive resources for meeting the net-short. The weightings are chosen based on the particular scenario, with heavy weighting to the commercial interest score used to model the current trajectory. DPV is one of the resources chosen to meet the net-short in the scenarios analyzed by PG&E in the BPP.
- GPC: The GPC IRP includes a program that specifically targets development of DPV. The quantity is chosen by GPC, somewhat arbitrarily, but the price paid will be developed using a competitive process. GPC will solicit bids for up to 50 MW of DPV systems. The price paid to the last bid will then be the basis for contracts for another 50 MW of DPV. GPC will cap the bid prices at its estimated value of solar. This program is therefore designed to increase DPV deployment without increasing costs. The value-of-solar estimate is based on results and tools used in the planning study to estimate the avoided energy, avoided capacity, avoided losses, and other costs and benefits of DPV. GPC developed the estimates for eight different tranches of 1,000 MW of PV and found a decline in the value with growing shares of PV.

Table 10. Approaches to Considering DPV as a Resource Option

Plan	Approach	Details
DEI 2015 IRP	Candidate Portfolio	Include significant DPV (2,480 MW, much more PV than in any other portfolio) in Stakeholder DG portfolio in response to stakeholder comments.
GPC 2016 IRP	Other	Set program goal for competitively bid DPV ²⁴ with bid price capped at estimated value of solar.
HECO 2013 IRP	CEM	Include two DPV options, residential (2 kW) or commercial (100 kW), in the Strategist CEM.
IPC 2015 IRP	Candidate Portfolio	Include DPV in stakeholder-driven candidate portfolio.
LADWP 2014 IRP	Candidate Portfolio	Include different FiT and NEM program targets in various candidate portfolios. The FiT cost is based on a 15-year cost forecast, and NEM cost is based on a "revenue loss" analysis.
NWPCC 7 th Power Plan	CEM	Include two DPV options, residential (5 kW) or commercial (32 kW), in the Resource Planning Model CEM.
NSP 2015 IRP	Candidate Portfolio	Include expanded DPV program levels in a candidate portfolio called the Preferred Plan. The cost of the programs, which varies from 12 to 20 cents/kWh, is included in the revenue requirement.
PG&E 2014 BPP	Other	Treat DPV as a resource via (1) a high DG forecast to reflect impact of more aggressive customer-sited DPV programs, and (2) including wholesale DPV as a resource option in the RPS Calculator used to meet the RPS net-short.
PSE 2015 IRP	CEM	Bundle DPV with other DSM program options with a similar levelized cost of electricity (based on the full cost of DPV without the ITC), then allow a CEM to select DSM bundles to include in a portfolio to meet energy and capacity needs.
TVA 2015 IRP	CEM	Include DPV, commercial-small and commercial-large, as an option in the System Optimizer CEM.

5.2 Including DPV as a Resource in T&D Planning

Increasingly, other planning entities are exploring ways to evaluate DPV as a resource option. The CAISO transmission-planning process, for example, first identifies transmission needs to meet reliability criteria and then examines additional DPV as one potential resource that could meet the reliability needs. If increased DPV can meet the needs, CAISO relays this information to other decision makers (the CPUC and utilities) so they can develop programs to increase DPV where it is needed. In this case, CAISO is only concerned with the feasibility of DPV meeting reliability needs; it leaves cost-effectiveness considerations to the other entities.

The California DRPs identify new processes for DG, including DPV, to be considered as a resource to meet distribution system needs. They have not considered distributed resources as options to meet distribution system needs to date, but they plan to revise their processes. The locational net benefit of distributed resources will be used to identify resource alternatives in distribution planning. Presumably, where the locational net benefits exceed costs, the resource is a cost-effective alternative to the traditional distribution investments. The location net benefit methodology is based on the Distributed Energy Resources Avoided Cost Calculator (DERAC)

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²⁴ The program includes both projects smaller than 3 MW that are competitively bid and an additional 50 MW of customer-sited DPV that is paid a fixed price, equivalent to the last winning bid in the competitive DPV process.

from the consulting group E3. DERAC includes components like energy value, capacity value, ancillary services, avoided losses, avoided RPS costs, avoided environmental impacts, and avoided T&D capacity. The base version of the tool uses system-level values, but the utilities will use location-specific components. The avoided T&D capacity will include factors like avoided distribution voltage and power quality capital as well as avoided reliability and resiliency capital. PG&E indicates that revisions to IEEE 1547 and the California Rule 21 interconnection rules may allow DPV to contribute to meeting voltage-regulation requirements through smart inverters. The plans also indicate that resources like DPV can increase the load-serving capability of the distribution system, but they cannot substitute for aging infrastructure replacement.

The New York Reforming the Energy Vision (NY REV) process²⁵ also establishes a process for DER, like DPV, to be considered as alternatives to traditional utility distribution investments. At the end of June 2016, the utilities filed Distribution System Implementation Plans that identify opportunities for DER to avoid traditional distribution investments. The plans list specific infrastructure projects by location, and they describe the process for identifying projects where DER will be considered as an alternative to traditional grid infrastructure. The plans also identify the performance criteria for DER needed to avoid the infrastructure project (for example, a certain amount of peak-demand reduction). Finally, the plans describe how the utilities will compare DER and traditional infrastructure investments through a utility-developed Benefit Cost Analysis handbook. The handbook will be consistent with a Benefit Cost Analysis framework outlined by the New York Department of Public Service Staff. The primary cost-effectiveness test will be the Societal Cost Test (SCT).

5.3 Distinguishing DPV from Other Resource Options

In order to consider DPV as a resource option, planners must distinguish it from other options, including utility-scale solar. Planners in our sample distinguish DPV in one or more of the following ways, which are assigned to each planning study in Table 9 (on page 30):

- Capital cost of DPV vs. UPV: The upfront cost of DPV is often higher than the cost of UPV owing to economies of scale. Eight utilities distinguish DPV from UPV based on the capital cost. The higher cost of DPV relative to UPV is the only way TVA and DEI distinguish DPV from UPV.
- Capacity factor of DPV vs. UPV: Planners often assume the annual energy production from DPV is less than the production from UPV due, at least in part, to the lack of tracking for DPV. Four utilities include different capacity factors for DPV and UPV.
- Capacity credit of DPV vs. UPV: Planners sometimes include a separate estimate of the capacity credit for fixed PV (which applies to DPV) and tracking PV (which applies to UPV). PG&E, NSP, NWPCC, and IPC use different capacity credits for UPV and DPV. IPC assumes that DPV with a southern orientation has a capacity credit of 28% compared

²⁵ The New York REV is a collection of initatives to increase the use of clean energy, increase the resilience of the grid, and enable customers to adopt distributed energy resources, among other goals. Portions of the REV involve the NY Department of Public Service, who regulates utilities in the state.

- with a 51% capacity credit for UPV, because it assumes tracking equipment would increase UPV production in the late afternoon when IPC's load is highest.
- Avoided losses: Losses are lower with DPV than with UPV or other resource options sited further from loads, as discussed in Section 9. Four studies assume that DPV avoids losses, a benefit that does not apply to UPV.
- *Transmission deferral:* DPV lessens the need for transmission investments or imposes less need for interconnection than UPV or other resources sited further from loads, as discussed in Section 8. Four studies either apply lower interconnection/transmission expansion costs to DPV or apply a transmission deferral value to DPV, distinguishing it from UPV and other resources sited further from loads.
- *Distribution deferral:* Only PG&E has DPV lowering expenses in the distribution system, as discussed in Section 8. This distribution-deferral value is included in the cost-effectiveness score for DPV resources in the RPS Calculator used to develop candidate portfolios that meet the RPS net-short.

The higher capital cost, lower capacity factor, and lower capacity credit assumptions for DPV all tend to make it less attractive than UPV. The benefits of avoided losses, transmission deferral value, and distribution deferral all tend to make DPV more attractive than UPV. DPV might also be considered as a resource to provide additional distribution system services (e.g., voltage regulation), or it might have a smoother aggregate output profile due to geographic smoothing that could reduce integration costs relative to UPV. However, none of the studies reviewed here discuss such benefits.

As described in Section 5.2, the California DRPs from PG&E, SCE, and SDG&E all mention factors like avoided losses and T&D deferral benefits in the proposed approaches to estimating the locational net benefits of DPV and other distributed resources. Similarly, the Benefit Cost Analysis Framework outlined in the NY REV for assessing the cost effectiveness of DER alternatives to traditional utility investments addresses a wide range of benefits and costs. The benefits of DER will include estimates of avoided capacity (including reserve margin), avoided energy, avoided T&D and related operations and maintenance, avoided T&D losses, avoided ancillary services, net avoided greenhouse gases, net avoided criteria pollutants, net avoided water impacts, net avoided land impacts, and net non-energy benefits. The costs of DER will include any program-administration costs (including incentives), added ancillary service costs, incremental T&D costs (including metering and communications), participant DER costs (reduced by rebates if included in program-administration costs), and non-energy costs (e.g., indoor emissions, noise).

Text Box 2. Community Solar as a Resource

Community or shared solar allows a customer to own, lease, or purchase a share of a PV system located on the premises of another customer or elsewhere in the power system. Community solar plants could be considered DPV (located near load, connected to the distribution system, and smaller than 5 MW), or they could be larger UPV plants. Community solar could increase the benefits and reduce the costs of PV. For example, community solar might be easier to site in beneficial locations through siting on utility property, targeting locations in development requests for proposals, having developers internalize interconnection costs, and including utility incentives or contract terms for plants in beneficial locations. Community solar that uses single-axis tracking might also have a higher capacity credit than fixed PV. These potential differences between community solar and rooftop PV are not discussed in significant detail in the planning studies, though several note pilot projects that may help inform future planning studies.

5.4 Determining the Cost Effectiveness of DPV as a Resource

Determining the cost effectiveness of DPV can be relatively straightforward if it is a supply-side resource: the planner can compare the cost of building and operating DPV compared with DPV's value or avoided costs. But how should a planner determine the cost effectiveness of a program that incentivizes customers to install behind-the-meter DPV, such as a rebate, NEM, or FiT program? This question is similar to the question of how planners should treat EE as a resource in planning studies. The primary guidance for considering cost effectiveness is the California Standard Practice Manual, which describes several cost-effectiveness tests (National Action Plan for Energy Efficiency 2007):

- Participant Cost Test (PCT): Is it worth it to the customer to install the resource?
- Ratepayer Impact Measure (RIM): What happens to rates and bills for non-participants?
- Utility Cost Test (UCT): Do total utility costs increase or decrease?
- Total Resource Cost Test (TRC): What are the net costs and benefits to the utility and its customers?
- Societal Cost Test (SCT): Are all of the benefits, including indirect benefits, greater than all of the costs?

Aside from the NY REV process, which explicitly states it will use the SCT to compare DER to traditional utility investments, the planning studies do not describe which test they use to determine cost effectiveness. Instead, we use information in the documents and our own judgment to identify which tests most closely parallel the way DPV is considered as resource in the planning studies.

As Table 11 shows, the TRC appears to be the most common approach to gauging cost effectiveness. However, using the TRC to evaluate the cost effectiveness of EE as a resource ignores non-monetary benefits a customer may include when choosing EE (Neme and Kushler 2010), and customers may similarly choose DPV even if its monetary benefits do not exceed its costs. By using the TRC, planners are essentially treating DPV as if it were an investment choice

only by the utility (like a supply-side resource) and potentially ignoring the factors that might drive a customer to invest in DPV.

Table 11. Apparent Cost-Effectiveness Tests Used to Evaluate DPV as a Resource

Entity	Cost-Effectiveness Test	Description
DEI	TRC	Includes the full cost of customers purchasing DPV in the PVRR of a candidate portfolio with DPV.
GPC	UCT	Compares the bid price from customers selling DPV power to the utility to the avoided utility costs.
HECO	TRC	Includes the full cost of customers purchasing DPV to characterize DPV in a CEM.
IPC	TRC	Includes the full cost of customers purchasing DPV in the PVRR of a candidate portfolio with DPV.
LADWP	UCT/RIM	Includes the full cost of DPV in the form of a FiT (UCT) and the lost revenue from NEM (RIM) to characterize different DPV programs in candidate portfolios.
NSP	RIM	Includes the incentives and compensation to DPV owners at the retail rate in the PVRR of candidate portfolios with DPV.
NWPCC	TRC	Includes the full cost of customers purchasing DPV to characterize DPV in a CEM.
NY DPS	SCT	Declares that benefit/cost analysis will use the SCT to compare DER to traditional utility investments.
PG&E	TRC	Compares the full cost of DPV to the avoided utility costs (including environmental compliance costs).
PSE	TRC	Includes the full cost of customers purchasing DPV to characterize DPV in a CEM.
TVA	TRC	Includes the full cost of customers purchasing DPV to characterize DPV in a CEM.

6. Incorporating the Non-Dispatchability of DPV into Planning Methods

Planner's question: How do you account for the variable and uncertain nature of generation from DPV when assessing its impacts on needs or its potential value as a resource?

One characteristic of DPV that distinguishes it from conventional resources is the non-dispatchable nature of its generation profile. DPV generation is *variable*, because its output changes with the level of sunlight and cloud cover, and *uncertain*, because the movement and size of clouds cannot be perfectly forecast. In the context of planning, non-dispatchability of DPV impacts the net load and therefore the need for other resources. This may include the need to burn fuel in conventional generators, use flexibility and/or ancillary services from other generators, and build T&D infrastructure. The non-dispatchable nature of DPV generation also means that its contribution to overall system adequacy will be less than its full nameplate capacity; its capacity contribution depends on the correlation between DPV generation system demand. When considering DPV as a resource, all of these impacts factor into the avoided cost or value of DPV. Planners have adopted a variety of practices to account for the non-dispatchability of DPV in studies.

This section discusses methods for addressing the hourly (Section 6.1) and sub-hourly (Section 6.2) characteristics of DPV. It also examines approaches for including the contribution of DPV to resource adequacy (Section 6.3) as well as other non-dispatchability issues addressed in planning studies (Section 6.4).

Innovations in Incorporating the Non-Dispatchability of DPV

Rather than a distinct innovative practice for incorporating the non-dispatchability of DPV in planning, innovation in this area is represented by evolving methods for capturing this important aspect of DPV in utility plans. Hourly DPV generation profiles allow for some potential integration issues to be included when evaluating portfolios with DPV, including multi-hour ramping impacts and overgeneration. LADWP highlights the overgeneration potential of low-load spring days and considers mitigation via EV charging during these periods. Combining hourly DPV profiles with detailed production cost models can help in evaluating the role of EVs and identifying times when overgeneration may be a concern. Impacts of DPV that are not captured with hourly generation profiles, such as sub-hourly variability and uncertainty, can be addressed through detailed integration studies. Finally, DPV's resource adequacy contribution can be evaluated using standard reliability tools to estimate the effective load-carrying capability (ELCC), which is the most rigorous way to estimate capacity credit.

6.1 Capturing the Hourly Generation Profile of DPV

A significant amount of the variability of DPV can be captured using an hourly generation profile, which can then be used in production cost models or CEMs to reflect the energy value of DPV. The hourly profile can also be used to calculate DPV's contribution to resource adequacy (the capacity credit) and other integration issues like ramping needs and overgeneration. These issues are prominent in the so-called California "Duck Curve," which shows the increasing

challenges from higher ramp rates in the net load during sunrise and sunset along with increased risk of midday overgeneration (CAISO 2016). The hourly generation profile can be used directly or subtracted from the hourly load to develop an hourly net-load profile.

Most planning studies in our sample appear to use an hourly DPV profile. One exception, TGT, only models DPV through a scenario in which customers add both DPV and storage and disconnect from the grid. In this case, TGT simply scales down customer demand in all hours, making an hourly DPV profile unnecessary. Some other utilities, particularly those with small forecasts of future DPV levels, appear only to adjust the average energy and capacity needs of the utility due to customers adding DPV, without taking into account the hourly DPV generation profile. These include DOM, DEI, ELA, and FPL.

A few utilities specify how they develop hourly DPV generation data. In all cases the hourly data are modeled PV production based on historical satellite-derived estimates of cloud cover, not actual PV plant output. ²⁶ Broadly applicable resources used by utilities in planning studies include NREL's System Advisor Model or PVWatts, PVSyst, and profiles from Clean Power Research ²⁷

The studies differ widely in how many sites are used to generate the hourly profiles. Geographic diversity of DPV sites can affect the aggregate hourly profile in ways that impact the energy value, capacity value, and integration needs of DPV. NV Power uses a single site (Reno, NV) for its generation profile, GPC uses five sites, NWPCC uses 16 sites, and TVA uses 26 sites.

Finally, two studies indicate that they developed hourly profiles based on PV system characteristics that matched current industry trends; in particular, they model systems with a higher inverter loading ratio (ILR). The ILR is the ratio of the PV array capacity to the PV system inverter capacity, and it is also known as the DC-to-AC (direct current to alternating current) ratio. A higher ILR indicates that the PV arrays are sized larger than the inverter capacity, which tends to clip PV production in hours with the highest insolation. The overall DPV generation profile therefore becomes slightly wider than it would be with a lower ILR. The ILR can affect the hourly net load shape, the capacity factor of DPV, and the capacity credit of DPV. The CEC uses an ILR of approximately 1.24–1.29 for fixed-tilt PV, and GPC assumes an ILR of 1.2. In contrast, the default ILR for PV systems in PVWatts is 1.1.

6.2 Adjustments for Sub-hourly Variability and Uncertainty

DPV systems also increase sub-hourly variability and uncertainty, factors not often considered directly within the planning tools used to evaluate portfolios in IRPs. Instead, planners sometimes introduce an "integration cost" to reflect the additional costs of managing increased

²⁶ Some planners would like access to actual PV production data, but they would need a protocol for data sharing.
²⁷ PAC and NSP use NREL's System Advisor Model. GPC uses commercial software called PVSyst with insolation data from NREL's Solar Prospector. TVA uses profiles from Clean Power Research. NWPCC uses NREL's PVWatts. The CEC developed hourly generation profiles, which PG&E uses in the BPP via the New Solar Homes Partnership incentive calculator.

sub-hourly variability and uncertainty, developed in detailed "integration cost studies."²⁸ It appears that these integration cost estimates are often applied when considering solar as a resource, though similar additional costs might be expected for market-driven DPV.²⁹ None of the integration costs focus specifically on DPV; rather, they are developed for solar in general.

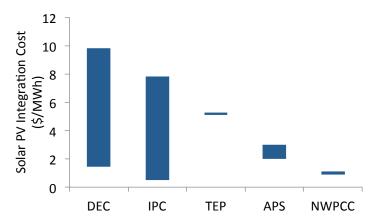


Figure 11. PV Integration Costs Used in Utility Planning Studies

Studies that quantify the operational integration costs of solar suggest a range of \$0.5-\$10/MWh (Figure 11). Within the same integration cost study, higher integration costs correspond to higher penetration, though the methods and other characteristics of the estimate also lead to differences across studies. These detailed studies can account for additional issues like sub-hourly variability, uncertainty, and flexibility needs. APS, for example, uses results from Black & Veatch to estimate additional costs of \$2/MWh in 2020 and \$3/MWh in 2030. The integration costs in that study account for the operating and capital cost of operating reserves to cover the sub-hourly variability of DPV and UPV (Black & Veatch 2012). IPC estimates an incremental integration cost for increasing tranches of solar ranging from \$0.5-\$7.8/MWh depending on the tranche. The integration costs are due to the cost for increasing the operating reserves that cover the hour-ahead scheduling uncertainty and sub-hourly variability of UPV (Idaho Power 2014). DEC estimates integration costs of \$1.43-\$9.82/MWh depending on the PV penetration and year (Lu et al. 2014). The integration costs in that study account for the operating cost of increased startups and shutdowns, operating reserves to cover the day-ahead uncertainty, and sub-hourly variability of DPV (Lu et al. 2014). 30 NWPCC uses a \$1/MWh integration cost that the Bonneville Power Administration applies to solar resources. That integration cost includes the operating and capital cost of providing additional operating reserves to manage the uncertainty of

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²⁸ The term integration cost is used in a variety of ways. Here we focus on the costs associated with managing the increased variability and uncertainty of solar in the bulk power system, because this is the most common meaning in the studies. As a result, these integration costs do not include factors like upgrading T&D equipment (addressed in Section 8) or the decline in the energy and capacity value of solar (addressed in Section 10).

Section 8) or the decline in the energy and capacity value of solar (addressed in Section 10).

29 The main difference is that market-driven DPV is usually treated as an adjustment to the net-load forecast prior to any analysis of the cost of candidate portfolios. Later in the studies, when solar is considered as a resource to meet forecasted needs, the planners discuss the integration costs associated with solar.

³⁰ In addition, Lu et al. (2014) use a "reference generation profile" that is different than PV's profile, which may result in some of the energy value (more specifically the difference in the energy value of PV and the energy value of the reference generator) being embedded in the integration costs.

hourly schedules and sub-hourly variability. TEP applies a \$5.2/MWh integration cost to solar, including fixed-tilt PV, based on the difference in production cost when using a flat average profile instead of an 8,760-hour profile. The integration cost does not include operating reserves to cover sub-hourly variability.

Other utilities discuss integration costs without providing values. GPC includes a "Support Capacity" cost in its estimate of the value of DPV, which appears similar in definition to other integration costs, though the values used are redacted. NV Energy implicitly increases costs by adjusting the regulation reserve requirements in its production cost model based on the amount of PV in a scenario, though no explicit integration cost is reported. Finally, SCE is currently conducting a detailed integration cost study that will help establish an integration cost to use in the California Long Term Procurement Planning process.

6.3 Contribution of DPV to Resource Adequacy

Almost all utilities assign a capacity credit³¹ to DPV that is less than its nameplate capacity. The capacity credit is most often used when considering DPV as a resource, though some utilities also apply the capacity credit to market-driven DPV when estimating resource adequacy requirements, net of the contribution of market-driven DPV. For the most part, the capacity credits described here are used in utility planning and capacity markets. Similar approaches are sometimes used to capture the reduction in peak load for T&D planning, though the methods for T&D planning often have variations, as discussed in Section 8.



Figure 12. DPV Capacity Credits Applied in Planning Studies

With the exception of winter-peaking utilities, the capacity credit of DPV in planning studies is 26%–50% of the nameplate capacity (Figure 12). The differing alignments of DPV generation

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³¹ Despite their similar names, the capacity factor and capacity credit of DPV should not be confused. The capacity factor measures how much energy a resource produces relative to what it could produce if generating at full capacity in all hours of the year. The capacity credit describes the contribution of PV to meeting the overall system peak requirements, which is heavily dependent on the coincidence between solar generation and electricity demand. Capacity credits for solar tend to be higher in summer-peaking systems and lower in winter-peaking systems.

with peak demand in each region are a major reason for the variability across studies. Methodological differences may also contribute to the variation. Two winter-peaking utilities assign a 0% capacity credit.

The reported capacity credit can vary by PV system characteristics. TVA, for example, assigns capacity credits of 50% to fixed-tilt DPV and 68% to single-axis-tracking PV. TEP applies a capacity credit of 33% to fixed-tilt PV and 51% to tracking PV. IPC accounts for orientation, reporting capacity credits of 28% for south-facing fixed PV and 46% for southwest-facing fixed PV, compared with 51% for tracking PV. FPL assumes a slightly higher capacity credit for DPV on commercial buildings (37%) than on residential buildings (34%) without explanation. APS and GPC note that capacity credit declines with increasing PV penetration, as discussed in Section 10.

The methods used to estimate DPV's capacity credit vary and are not always described. A few utilities, including APS and GPC, appear to use detailed reliability-based models that calculate the ELCC of DPV, which is the most rigorous way to estimate capacity credit. Others—such as IPC, ISO-NE, and TVA—describe methods that focus on DPV production during a set of peak hours. For NVP and PAC, the capacity credit is implicit in the way they estimate capacity needs from the peak net load, after reducing the load by the hourly DPV profile. The peak-net-load method is seen in utility resource planning studies and in some transmission planning studies, but this approach may overemphasize the 1 peak hour of the year relative to probabilistic reliability methods.

6.4 Other Non-Dispatchability Issues Addressed in Planning Studies

Other integration-related issues are discussed in the planning studies. LADWP identifies overgeneration—when the system cannot absorb all available renewable energy—as an issue on low-load spring days. It explores this issue with the hourly PV production data and a detailed production cost model (Prosym). One strategy LADWP considers to mitigate overgeneration is electric vehicle (EV) charging. The two portfolios with the highest share of renewables are also assumed to have the largest increase in EV adoption, and EVs may enable load shifting and absorbing of overgeneration from renewable resources. LADWP also expects other technologies might help—including EE, storage, and static capacitors and reactors—and highlights the need to better understand the integration needs of DPV and other variable renewables. PSE includes estimates of flexibility demand from varying load and renewables as well as flexibility supply from its portfolio of resources. Several of the resource planning studies also discuss integration challenges with DPV at the conceptual level. APS points to an increased need for flexible resources. DEI indicates a need for resources to offset ramping effects of solar such as storage or flexible combustion turbines.

In a few cases, utilities suggest pilot studies for better understanding integration challenges and solutions. FPL, for example, plans to conduct a pilot study with PV and storage at a commercial

³² In some cases, the utilities also conduct or participate in detailed integration studies in parallel to the standard planning process. A few examples include HECO (Eber and Corbus 2013), DOM (Navigant 2016a, 2016b), DEC/DEP (Lu et al. 2014), and APS (Black & Veatch 2012).

customer site. It will use data generated in the project to develop operational best practices for addressing any potential problems identified in the pilot. ELA also plans a DPV and storage pilot to determine the viability and performance of the technologies in Louisiana.

7. Accounting for Location-Specific Factors of DPV

Planner's question: How do you account for the fact that the benefits and impacts of DPV can vary depending on location? How do you predict where DPV will be located?

For the majority of IRPs, the specific location of DPV is not important, because IRPs generally focus on meeting system-level needs. The rare exceptions are where the resource planners attempted to use location-specific factors to distinguish different DPV options or distinguish DPV from other resources. Location can matter in estimating avoided losses, avoided T&D costs, the DPV generation profile, and the capacity credit. In T&D planning, however, the location of DPV is much more important. For independent system operators (ISOs) that operate capacity markets or plan the transmission system, the location of DPV matters down to the granularity of dispatch or load zones. ³³ Location down to specific feeders is important for distribution planners.

This section reviews the approaches used by planners to identify where DPV will be located (Section 7.1). We describe a few examples of how location-specific factors are then used in planning (Section 7.2). In addition, we highlight a few examples of potential ways to incentivize siting of DPV in the most favorable locations (Section 7.3).

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³³ Load zones represent large areas within the footprint of the ISO where transmission is usually not a constraining factor for delivering generation to load during peak times. Loads often pay for energy based on the load zone price rather than the nodal price used for generators.

Innovations in Predicting and Influencing Future DPV Locations

Simple methods for predicting the locations of future DPV proportionally allocate the deployment based on the locations of existing load, population, or DPV. Innovative approaches employ additional predictive factors as well, such as demographics and customer load, as summarized in Table 12 and described in Section 7.1. Utilities that use such innovative "propensity to adopt" analysis include PG&E, SCE, and SMUD. Another emerging utility innovation is locating DPV strategically to enhance its benefits. Organizations exploring this tactic include DEI, DOM, PG&E, GPC, and ISO-NE—generally focusing on utility-owned systems. A recent pilot project in Rhode Island demonstrates how promotion of strategic locations for behind-the-meter DPV can help defer feeder upgrades (Text Box 3).

Table 12. Factors Used by Various Methods for Predicting Future DPV Locations

Method	Description	Predictive Factors Used		
		Location of existing load or population	Location of existing DPV	Detailed customer characteristics
Proportional to Load	Assumes DPV is distributed in proportion to load or population	X		
Proportional to Existing DPV	Assumes DPV grows in proportion to existing DPV		X	
Propensity to Adopt	Predicts customer adoption based on factors like demographics or customer load	X	X	X

7.1 Estimating the Location of Future DPV

The resource planning studies that are the primary focus of many of the other sections provide little insight into how planners account for location-specific factors. T&D planning studies, including studies by ISOs for transmission and capacity market planning, provide more details on projected DPV locations and are the primary source of information for this section. Here we focus only on methods to identify where DPV, sited primarily behind the meter, will be located within the system—methods to estimate the aggregate quantity of DPV are discussed in Section 3. Below we describe the three basic methods for estimating the location of future DPV along with examples of real-world use. Table 13 compiles the methods used across the plans we reviewed.

Proportional to load: This method assumes DPV is distributed in proportion to load or population. Barring other information, it may be reasonable to expect that DPV growth will occur where more customers and load are concentrated. GPC allocates DPV to five major population centers in the state, with most DPV located near Atlanta. PG&E in the BPP allocates DPV to specific substations proportional to the substation peak load. The aggregate quantity of DPV comes from a DPV forecast specific to its service territory. PJM allocates state-level DPV

forecasts to PJM load zones in proportion to the peak demand. SDG&E assumes that future DER, including DPV, would be evenly dispersed across its service territory and its distribution system in its DRP.

Proportional to existing DPV: This method assumes DPV grows in proportion to existing DPV or based on recent interconnection requests. Additional factors like customer demographics, availability of rooftops, and activity of local DPV marketers could impact the deployment patterns of DPV. A simple way to account for these factors is to assume that future DPV will tend to be installed near where DPV has been installed in the past. NYISO allocates DPV to its 11 load zones in proportion to the existing DPV in those load zones. A slight variant on this approach, used by ISO-NE, is to allocate DPV to 19 dispatch zones based on a survey of DPV in interconnection queues from distribution system owners. PG&E's DRP assumes that wholesale DPV will be located similarly to the most recent winning bids from the renewable auction mechanism solicitations. HECO, in its Distributed Generation Interconnection Plan, applies a single DPV growth rate across its service territory.

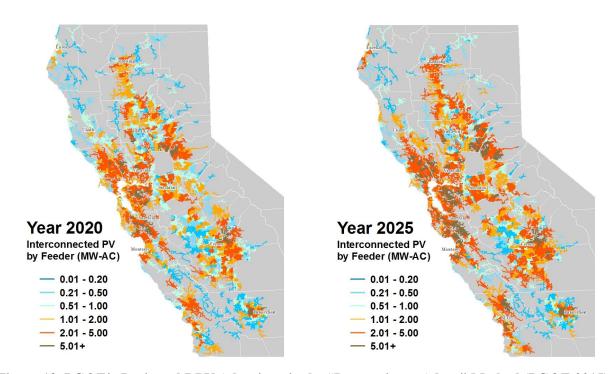


Figure 13. PG&E's Projected DPV Adoption via the "Propensity to Adopt" Method (PG&E 2015)

Propensity to adopt: With additional data at the city, neighborhood, or even individual household level, it is possible to estimate the propensity of a household to adopt DPV based on directly observable factors like demographics or customer load. PG&E, in its DRP, uses a logistic regression to predict the probability of a customer adopting DPV. For residential customers, the predictive factors include information about housing, customer demographics, electricity consumption, and geography. For non-residential customers, the factors include customer sector, electricity consumption, and tariff. PG&E fits the regression using information about previous DPV adopters and then applies it to all customers to estimate the probability of adoption (Figure 13). It then selects customers with the highest probability to adopt until the

amount of DPV adopted matches the aggregate DPV adoption forecast for the utility. PG&E's approach is guided in part by similar research from NREL (Davidson et al. 2014).

SCE follows a similar approach in its DRP, though it provides less detail on how the propensity of individual customers to adopt DPV is estimated. SMUD worked with Black & Veatch to develop feeder-level estimates of DPV adoption (Wilson et al. 2015). Like PG&E, they develop a propensity to adopt and use it to identify which customers will adopt DPV up to the aggregate DPV forecast (developed through other means, see Section 3). In the model, propensity to adopt is based on demographic factors that are assigned to different Nielsen PRIZM market-segmentation datasets. The PRIZM dataset categorizes households into one of 66 different "demographically and behaviorally distinct types" that can be used to discern customer behaviors and purchasing preferences (Nielsen 2016). Then, a diffusion factor increases the probability of adoption based on the number of PV systems within a specified influence radius. For each year of the forecast, specific homes are selected to adopt DPV based on a random number draw dependent on the probability of adoption. The diffusion factor for the next year then depends on which customers adopted in the previous year.

More advanced methods for estimating the location of DPV adoption, in addition to the quantity, are discussed in Section 3.5. These include bottom-up agent-based models (e.g., Rai and Robinson 2015) and top-down statistical models (e.g., Higgins et al. 2014, Graziano and Gillingham 2015).

Table 13. Methods for Estimating the Location of Future DPV

Plan	Method	Details
GPC 2016	Proportional to load	Location is a factor in avoided losses and avoided transmission estimates for DPV. GPC assumes DPV is distributed across five major load centers in Georgia (with 63% in Atlanta).
HECO Distributed Generation Interconnection Plan 2014	Proportional to existing DPV ³⁴	The growth rates of DPV are applied uniformly across each company without detailed projections by circuit or specific areas in distribution system modeling.
ISO-NE 2015	Proportional to existing DPV	Location is a factor in the capacity market and transmission planning. ISO-NE allocates the DPV forecast to 19 dispatch zones (each within a state) based on a survey of distribution owners' interconnection queues.
NYISO 2015	Proportional to existing DPV	Location is a factor in the capacity market and transmission planning. NYISO allocates DPV to 11 load zones in proportion to the existing DPV in the load zone.
PG&E BPP 2014	Proportional to load	DPV forecasts are made by utility load zone, but then DPV is allocated to specific substations proportional to the peak load. The RPS calculator includes location-specific T&D costs that are used to affect the resource ranking.
PG&E DRP 2015	Propensity to adopt & proportional to existing DPV	Aggregate DPV forecast is allocated to distribution feeders based on an estimate of a customer's propensity to adopt DPV. Wholesale DPV is assumed to be located in areas similar to the most recent results from the renewable auction mechanism solicitations.
PJM 2015	Proportional to load	Location is a factor in the capacity market and transmission planning. PJM allocates state-by-state forecasts of DPV to PJM load zones proportional to the peak demand. The peak demand in that load zone is then reduced by the on-peak contribution from DPV (based on historical DPV production for the hour ending 5 pm during June–August).
SCE DRP 2015	Propensity to adopt	Aggregate DPV forecast is allocated to distribution feeders based on an estimate of a customer's propensity to adopt DPV.
SDG&E 2015	Proportional to load	SDG&E states that DPV forecast is allocated evenly across the utility service territory and the distribution system, which we interpret as proportional to load.
SMUD 2015	Propensity to adopt	Aggregate DPV forecast is allocated to distribution feeders based on an estimate of a customer's propensity to adopt DPV. Propensity is based on household classification into different market segments (PRIZM) and adoption by neighbors.

7.2 Using Location of DPV in Planning

The location of DPV matters in capacity markets, transmission planning, and distribution planning. Because the avoided costs of DPV depend on its location, location can also influence the relative attractiveness of DPV as a resource in IRPs.

Only the GPC and PG&E IRPs bring location-specific information into the evaluation of DPV. PG&E uses location-specific losses, transmission costs, and avoided distribution costs to affect the relative cost ranking of DPV resources in the RPS Calculator. These parameters are specific to the individual competitive renewable energy zone or the utility service territory within the calculator. GPC uses the assumed DPV location in estimating avoided losses and avoided

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³⁴ A similar assumption was made in HECO's 2016 PSIP.

transmission for DPV in the value-of-solar calculations that set maximum bid prices for procuring DPV.

Capacity markets and transmission planning require DPV locations down to load-zone levels. ISO-NE and NYISO use the load-zone-level DPV forecast in their capacity markets and transmission planning. PJM adjusts the load-zone peak demand by the on-peak contribution of DPV for its capacity market and transmission planning.

Distribution planning requires feeder-level forecasts of DPV adoption. The California DRPs describe a process to incorporate DPV forecasts into estimates of the peak demand on feeders. In addition, location-specific DPV forecasts can be used to identify where the capacity of the distribution system to accommodate DPV without upgrades, the "hosting capacity," is likely to be limited relative to projected growth. This allows for either proactive upgrades or signaling to the market where interconnection may be more challenging. Both topics are addressed further in Section 8.

7.3 Strategically Locating DPV

Edge et al. (2014) outline several options for strategically locating DPV, including online maps showing DPV feeder penetration, targeted interconnection processes, locational incentives, locational interconnection costs, power-purchase rates that differ by location, and proactive distribution upgrades with costs allocated to the beneficiaries of the upgrades. Most of the strategies are useful for in-front-of-the-meter DPV or DPV that is utility owned, while only a subset, like targeted interconnection processes or locational incentives, are applicable to behind-the-meter DPV.

Somewhat unexpectedly, we find some discussion of strategically locating DPV in resource planning studies. One option suggested by DEI is utility ownership of DPV, where the utility could choose locations that provide the most benefits. DOM's Solar Partnership Program is a 5-year demonstration program to study the benefits and impacts of utility-owned solar DG on targeted distribution circuits. PG&E's BPP uses the RPS Calculator to evaluate potential DPV resources where the cost metric is influenced by location-specific losses, transmission costs, and avoided-distribution benefits. GPC mentions that estimates of DPV interconnection costs can be used in the evaluation of DPV bids to identify which locations are more cost effective. ISO-NE suggests that its identification of system needs, including capacity and transmission, across different load zones can signal where it expects resources can provide the greatest benefit and where wholesale prices will tend to be higher. This may help incentivize in-front-of-the-meter DPV. However, other incentive mechanisms, as discussed by Edge et al. (2014), will be needed to influence the location for behind-the-meter DPV.

Finally, in the distribution planning process outlined in the NY REV and the California DRPs, the utility is to highlight where there is potential for DPV to offset investments. The location-specific value analysis (the benefit-cost assessment for NY REV and the locational net benefits for the California DRPs) will then show a higher assessment of benefits in locations where DPV is likely to defer or avoid the greatest costs. The next challenge is determining how to direct projects to those areas that have the greatest locational benefits. One recent pilot project from Rhode Island provides a viable approach (Text Box 3).

Text Box 3. Strategic Siting of DPV to Defer Distribution Upgrades

Rhode Island, through the Office of Energy Resources (OER), recently implemented a pilot project to demonstrate that strategically sited DPV can defer a \$2.9 million distribution upgrade (Musher 2016). The pilot project builds on an existing "DemandLink" program from National Grid, which deploys EE and demand-response resources as non-wires alternatives where cost effective. The DemandLink program was in part developed in response to a legislative "Least Cost Procurement Mandate" that involves the evaluation of non-wires alternatives.

Currently, two feeders serve approximately 5,200 customers in two communities. Projected load growth would have led to an overload in 2014, which could be mitigated by adding a third feeder. The peak loads driving the upgrade occur in summer months during late afternoon and early evening. The non-wires alternative required 150 kW of load relief from the customers in 2014, growing to 1 MW in 2018, to defer the upgrade for 4 years.

OER designed the DPV pilot project to involve two approaches for incentivizing DPV deployment in the program area: a competitive solicitation and a targeted "Solarize" campaign. In both cases, the pilot was designed to incentivize DPV system designs that would provide the most load relief in late afternoon hours (e.g., west-facing panels). For the competitive solicitation, OER solicited applications for smaller-sized groundmounted solar installations (less than 0.5 MW). It selected a 250-kW single-axis tracking project that required the smallest grant to deploy a system that was most aligned with the load profile of the feeder. The "Solarize" campaign incentivized a westfacing orientation of rooftop PV systems by compensating system owners for lower production and bill savings relative to a south-facing system. The "Solarize" campaign led to the installation of 67 rooftop systems totaling 485 kW, which was twice as much participation as the program administrators originally planned. Altogether the DPV pilot is expected to contribute 362 kW of peak-load reductions toward the deferral of the distribution asset upgrades. The performance of this pilot will be evaluated in 2016 and 2017, and the positive experience so far is likely to inform development of Rhode Island's Common Cost-Benefit Framework.

8. Estimating the Impact of DPV on T&D Investments

Planner's question: How do you evaluate the impact that DPV will have on the need to invest in the T&D system?

Because DPV is often located on the distribution system, close to loads, its impact on the T&D system is different than the impact of utility-scale resources. Furthermore, because the distribution system was traditionally designed to accommodate only the flow of power from the transmission system to the customer, locating DPV on the distribution system fundamentally changes traditional approaches to distribution planning. Three key questions relate to the increasing impacts of DPV on the T&D system:

- *System needs:* How does DPV impact the traditional drivers of investments in the T&D system?
- *Interconnection:* How much DPV can be accommodated on the existing distribution system?
- *Proactive planning for DPV*: What investments are needed to accommodate more DPV on the distribution system?

Various T&D planning studies are beginning to address these questions. This section summarizes the range of approaches used or proposed in these studies, and it highlights some innovative approaches.

Innovations in Estimating the Impact of DPV on T&D Investments

Innovations in estimating the impact of DPV on T&D investments apply differently to different organizations, depending on each organization's current progress in this area as well as its projected deployment of DPV and the relative robustness of its T&D infrastructure. For organizations that have not yet considered DPV in T&D studies, innovative examples of such planning are available from numerous planning entities, as described in Section 8.1. Likewise, organizations that find themselves needing to calculate hosting capacity—the amount of DPV that can be interconnected to the distribution system without violating operating limits—can draw on innovative studies from their peers. These include the use of hosting capacity analysis to both screen and steer the location of DPV (see Section 8.2). At the most advanced end of the spectrum, some organizations are already proactively planning investments to accommodate additional DPV. Innovative analyses by Pepco, DOM/Navigant, and HECO calculate the cost of various options for increasing the hosting capacity, including the impacts of advanced inverters and energy storage (see Section 8.3).

8.1 System Needs: Impact of DPV on Traditional Drivers of T&D Investments

Adding DPV on the distribution system near loads reduces demand for electricity from the bulk power system that would otherwise need to be moved over the T&D system to customers. Accounting for this decline in demand can defer or eliminate the need to build new transmission or distribution infrastructure. Here we describe how planners are beginning to account for DPV in their T&D planning studies so these benefits can be realized. In Section 8.2, we describe

efforts by utility planners to assess how much DPV can be accommodated on the distribution system before it triggers the need for new T&D investments.

8.1.1 Impact of DPV on Drivers of Transmission Investments

Transmission planning primarily focuses on satisfying reliability requirements, with supplementary studies that consider the economic benefits from expanding transmission (e.g., lower congestion costs) or the need to expand transmission to support public policy goals (e.g., accessing low-cost renewables to meet state RPS goals). Reliability-based transmission planning often focuses on the operation of the transmission system during forecasted peak-load conditions (additional scenarios might examine off-peak, but still stressful, conditions). The studies aim to ensure operation is within limits during normal operation and during contingencies. When operation falls outside of the limits and results in a violation, transmission planners identify solutions, like investment in additional transmission capacity, to mitigate the violation. Because adding DPV to the system can lower the peak load, planners may include forecasts of DPV in determining the peak load for the reliability studies.

Increasingly, transmission planning entities are beginning to account for DPV forecasts in transmission planning studies, including ISO-NE, NYISO, PJM, CAISO, NV Energy, WECC, and HECO. For the most part, these studies consider a single forecast of DPV adoption, though HECO considers the robustness of transmission investment needs by examining extreme bookend scenarios with high or low DPV adoption (as discussed in Section 4). HECO finds, for some islands, that transmission is needed in the scenario with low DPV adoption but is not needed in the scenario with high DPV adoption. Approximately \$152 million of transmission upgrades over the 10-year planning period are needed to accommodate load growth in the low-DPV scenario, but these are not needed in the high-DPV scenario. GPC similarly identifies transmission needs with and without incremental DPV tranches to quantify the incremental avoided transmission cost of DPV in their value-of-solar calculations. The magnitude of the avoided transmission cost, however, is not public. WECC includes DPV adoption in a reference case and a high-DPV case used to study future transmission congestion. The high-DPV case increases congestion on some transmission lines in Southern California where solar penetrations are high.

The location of DPV can be important to consider in transmission planning studies. The various approaches used to estimate the location of future DPV are discussed in Section 7.

In addition, DPV generation during periods of peak demand is an important consideration. For the most part, transmission planners appear to use the same methods used to estimate the capacity credit to account for reduced peak demand with DPV (as discussed in Section 6). There are some variations, however. ISO-NE, for example, estimates the capacity credit of DPV for the forward capacity market based on production between 2 and 6 pm in summer months, leading to a capacity credit of 40%. But in the transmission planning, it uses DPV production in a narrower window, between 4 and 6 pm in summer months, to estimate the reduction in peak demand, which is only 26% of the solar nameplate capacity. PJM uses DPV generation during 4–5 pm for

³⁵ The methods used by these planners to develop the forecasts are addressed in Section 3.

June—August to estimate the capacity credit for the capacity market. However, PJM uses extreme summer peak-load conditions for its transmission base case, where DPV's contribution is estimated based on generation in the peak hour of the 10 highest load days in the previous year. Both ISO-NE and PJM consider a winter case too, in which DPV generation during winter is assumed to be much lower than during the summer peak.

8.1.2 Impact of DPV on Drivers of Distribution Investments

Distribution planning is largely driven by forecasts of peak load relative to the distribution system capacity. The traditional distribution planning process, as described in the documents we reviewed, is often an annual process where planners forecast peak-load growth on distribution feeders or substations and then assess whether the distribution system can manage expected growth over the next 1–5 years (with less-refined assessments out to 10 years). The planners then identify options for reconfiguring the distribution system to move load from overused to underused feeders or projects needed to add capacity to the distribution system.

One document, PG&E's DRP, describes how in current practices the planners forecast peak-load growth starting with the observed peak load at substations, without explicitly accounting for DPV. Because existing DPV on some feeders lowers the observed peak load, the forecasts of peak load are lower than they would have been without DPV. As a result, the forecasts already, to some extent, account for recent additions of DPV when planning the distribution system. ³⁶ Going forward, the utility plans to include explicit forecasts of DPV in the peak-load forecasts used for distribution planning, which will help ensure that distribution system upgrades that can be deferred by customer adoption of DPV are deferred.

Distribution planning is somewhat more straightforward than generation planning, because options for increasing distribution capacity can largely be compared based on capital cost. Resource planning decisions, on the other hand, depend on capital cost, operating cost, and impacts on the dispatch of other resources. Furthermore, distribution planning focuses on a shorter horizon than does resource planning. While planning horizons vary across utilities, distribution planners tend to focus on distribution needs in the upcoming 1–2 years, with a broader outlook over the next 5–10 years, while resource planners focus on system needs over the next 10–20 years. Forecasting challenges and uncertainty may therefore be larger in a resource planning context than for distribution planning.

The economic value of DPV in deferring distribution system investments is largely derived from the time value of money: the deferral value of DPV will be greatest on feeders where the current peak load is near the capacity of the distribution system and where DPV production is coincident with the peak load on the feeder (Figure 14). DPV's deferral benefits will be much lower where the peak load of the feeder is well below the feeder capacity, where DPV is not coincident with

³⁶ This contrasts with PJM's approach, which separates the load and DPV forecast. PJM is very careful at the transmission level to first "reconstitute" the load by adding in estimated historical DPV production. It uses the reconstituted load to create the load forecast. Then, the net load forecast is estimated by bringing in historical DPV plus the forecast of DPV growth (Falin 2015).

peak load, or where feeders must be upgraded owing to aging infrastructure issues rather than insufficient capacity.

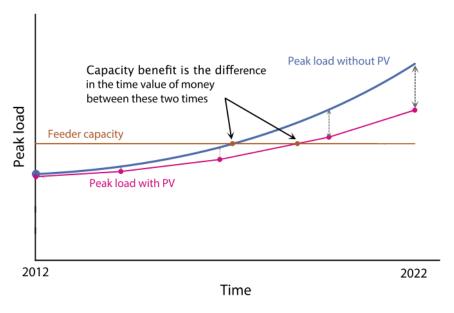


Figure 14. Illustration of the Distribution Capacity Deferral Value of DPV (from Cohen et al. 2016)

The NY REV process provides guidance on how to estimate the avoided distribution capacity value of DER in the Benefit Cost Analysis Framework. It highlights the need for utilities to estimate the value of avoided T&D based on the latest detailed marginal-cost-of-service studies. As described above, one of the primary drivers of this cost will be how close the system is to reaching capacity. Reducing the peak load for equipment that is near capacity will provide more deferral value than reducing it for equipment with significant excess capacity. For a particular DER application, the avoided investment cost then depends on the generation during the single hour of peak demand. Whether this hour of peak demand is based on the coincident system peak or the local non-coincident peak depends on the design criteria of the equipment. For example, deferral of a transmission line would depend on the reduction in the transmission system peak, whereas deferral of secondary distribution cables would depend on reduction in a new customer's non-coincident peak demand.

An emerging issue is how to consider DPV as a resource that can be used to meet T&D needs. Once distribution planners have identified a need for upgrades to T&D, what process is available for DPV to be evaluated as a potential alternative to traditional T&D investments? These questions are addressed in Section 5.

8.2 Interconnection: How Much DPV Can Be Accommodated?

Growing deployment of DPV raises concerns about two-way power flows and other concerns regarding distribution systems that were originally designed only to deliver power from substations to customers. These concerns often lead to conservative limits on how much DPV can interconnect to a feeder, with additional detailed studies required for interconnection

requests beyond the limits. Owing to their time-consuming nature, these studies can become a barrier to DPV deployment.

To address this, some distribution planners are beginning to undertake hosting capacity analysis to streamline the interconnection process and better inform stakeholders, developers, and customers. Hosting capacity refers to the amount of DPV that can be interconnected to the distribution system without violating operating limits including voltage, thermal, and protection limits. In general, these studies are performed by simulating the operation of a distribution system with increasing additions of DPV at random locations throughout the feeder. As shown in Figure 15, the minimum hosting capacity is the highest DPV penetration where, no matter where the DPV is located, no violations occur. Additional DPV deployment will begin to produce violations, depending on where the DPV is located. The maximum hosting capacity is the penetration where any additional DPV will lead to violations, irrespective of where the DPV is located (EPRI 2015). HECO recently completed a hosting capacity analysis for all feeders in its system. The California DRPs, the NY REV process, and Massachusetts' grid-modernization plans all highlight a role for hosting capacity analysis.

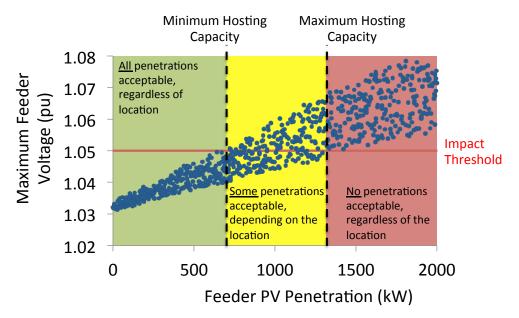


Figure 15. Illustration of Hosting Capacity Analysis (adapted from EPRI 2015)

Hosting capacity analysis can be used in two ways: as an interconnection screen and to steer development. When DPV on a feeder is below the minimum hosting capacity, additional DPV, by definition, can be located anywhere on the feeder without causing violations. Thus, interconnection requests can be expedited where DPV is below the hosting capacity, whereas additional study and/or additional equipment may be needed when DPV exceeds the minimum hosting capacity.

Providing an estimate of the hosting capacity to stakeholders, developers, and customers can also help steer development to locations with adequate hosting capacity. A number of utilities suggest that they plan to integrate hosting capacity analysis into their distribution planning tools and

eventually develop publicly accessible maps of hosting capacity. Distribution planning tools specifically mentioned for conducting hosting capacity analysis include CYME and Synergi. While some of the California DRPs conduct a hosting capacity analysis for every distribution feeder, SCE conducts detailed studies on select representative feeders (30) and extrapolates the hosting capacity to all other feeders (4,636) based on features like voltage class, climate zone, circuit loading, transformer capacity, circuit miles, customer mix, and distribution equipment. Navigant (2016a) similarly identifies a select number of representative feeders (selecting 14 to represent 1,813) to study the impact of DPV on DOM's system. Navigant uses a clustering algorithm to select the representative feeders such that simulation results for the representative feeder are expected to be comparable to all other feeders in the cluster. Clustering is based on 11 different properties of the feeders, including voltage class, circuit miles, load, and ratio of the high voltage to low voltage on the feeder.

8.3 Proactive Planning for DPV: Investments to Accommodate More DPV

Some regions have specific policy goals to allow for more customer choice, including installation of a DPV system. Under these circumstances, the utility may need to proactively plan to expand the hosting capacity of the distribution system in a least-cost manner. Hosting capacity studies can identify which violations currently limit penetration of DPV (e.g., voltage, thermal, protection). Additional studies are then required to identify options to mitigate those violations and the cost of each option. For example, if the hosting capacity is limited by older protection equipment that does not operate properly with two-way flow from a distribution feeder to a transmission line, then the hosting capacity can be expanded through options like new protection equipment that allows two-way power flow or storage on the feeder to absorb excess generation.

Pepco, through a U.S. Department of Energy Sunshot grant, used distribution planning software from Electrical Distribution Design (EDD) to identify the base hosting capacity for 20 different feeders on its system. They then found the incremental increase in hosting capacity and incremental cost of implementing several alternative measures. These include using dynamic load tap changer set points, changing voltage regulator settings, having smart inverters operated with a fixed, absorbing power factor of 0.98 (instead of 1.0), and using a small battery storage system on the distribution system (Steffel et al. 2015).

Navigant conducted a similar study for DOM based on 14 representative feeders (Navigant 2016a). First, the Synergi distribution system model is used to estimate the hosting capacity of the representative feeders, based on the penetration at which additional PV would trigger the need for upgrades to address violations in thermal, voltage, or operational limits. Then, more DPV is progressively added to the feeder, and the system upgrade costs to address violations are noted. The system upgrade costs include traditional measures such as line reconductoring, load balancing, adding additional phases, and adding voltage-regulating devices. The upgrade costs using these traditional measures are shown for all 14 feeders in Figure 16.

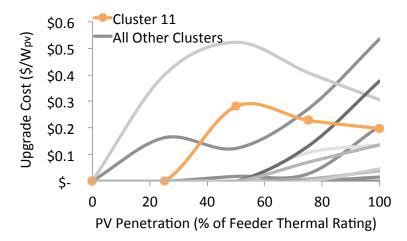


Figure 16. Estimated Costs to Increase the Hosting Capacity of 14 Representative Feeders for DOM (adapted from Navigant 2016a)

Navigant also examines the upgrade costs for a select set of feeders assuming use of DPV with advanced inverters capable of supporting voltage through power factor control (Adv. Inverter) or that both batteries and advanced inverters are available (Adv. Inverter + Storage). As shown in Figure 17, the availability of advanced inverters could substantially lower the upgrade costs and increase the hosting capacity on a particular feeder, representing cluster 11. Adding storage does not lower the upgrade costs (assuming advanced inverters are available). Navigant notes, however, that taking advantage of advanced inverters requires that the utility invest in system-wide telecommunications and distribution management systems that are neither currently available at DOM nor included in the upgrade cost estimates. Strategies to roll out advanced inverters at various U.S. utilities are described by Edge et al. (2015).

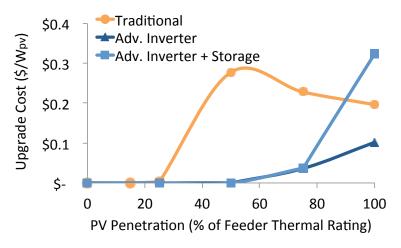


Figure 17. Comparison of Traditional Upgrade Costs to Costs with Emerging Technologies for Cluster 11 (adapted from Navigant 2016a)

In a similar analysis, HECO identifies the cost of increasing the hosting capacity of its distribution systems. It first identifies conditions that would trigger the need for upgrades and then uses forecasts of DPV adoption, including expectations for grid-friendly inverters, to identify how many distribution feeders would hit triggers as well as the cost of the upgrades. The total upgrade costs to 2030 are projected at around \$200 million, assuming that all customers

with DPV continue to export power to the grid as they have in the past. HECO also identifies how much lower the upgrade costs would be for different shares of customers that are assumed to be "non-export" customers who use all DPV onsite. Presumably the non-export customers would use technology like solar plus storage or solar plus load controls to reduce the share of exports. The upgrade costs with non-export customers are substantially lower. HECO uses Synergi for steady-state analysis and PSS/E for transient and dynamic analysis in its studies.

9. Estimating the Avoided Losses Associated with DPV

Planner's question: How do you estimate the impact of DPV on power system losses?

Siting PV near loads avoids losses that would otherwise occur between generation at the bulk power system level and consumption at the consumer level, and this distinguishes DPV from other generation resources, including UPV. A Navigant study for DOM, for example, shows greater avoided losses for DPV, located near loads, than for the same quantity of UPV, located in more rural areas with available land (Navigant 2016b). That said, DPV can increase losses if sited in areas that tend to export significant amounts of power or losses can increase with higher DPV penetration levels.

Reducing losses lowers both the amount of energy and the capacity needed at the bulk power level. One important characteristic of losses is that they increase non-linearly with increased load on T&D lines. This in turn has two important implications. First, a small reduction in load reduces losses by the marginal loss rate rather than the average loss rate. The non-linear relationship means that the marginal loss rate is different, and often higher, than the average loss rate. The second, reductions in load during heavily loaded times reduce losses to a disproportionately greater extent than reductions in load during light-load times. The ability of DPV to avoid losses therefore depends not only on its proximity to load, but also on the correlation of DPV generation with times of high load.

³⁷ This depends on how high the fixed losses are in the system, but, if the variable (I²R) losses dominate the fixed losses, then the marginal loss rate will exceed the average loss rate.

Innovations in Estimating Avoided Losses Associated with DPV

Because of the non-linear variation of line losses with load, the most comprehensive estimation of system losses—and thus the potential avoided losses with DPV—is a time-differentiated marginal loss rate, as shown in Table 14. However, none of the studies we evaluate appear to use a marginal loss calculation. This represents an area for future innovation. One utility, PSE, provides a detailed circuit-level analysis of losses, which offers a different refinement at a relatively small scale.

Table 14. Characteristics Addressed by Various Methods for Estimating System Losses

Method	Description	Loss Characteristics Addressed		
		Varied losses over time	Marginal loss rate differs from average	Circuit- level losses
Average Loss Rate	Applies single average loss rate across all hours of the year			
Time-Differentiated Average Loss Rate	Differentiates average loss rate based on timing of avoided losses	X		
Marginal Average Loss Rate	Applies an average marginal loss rate based on line loading		X	
Time-Differentiated Marginal Loss Rate	Differentiates marginal loss rate by hour, month, or "peak" vs. "energy"	X	Х	
Detailed Analysis of Losses	Uses a circuit-level model to analyze losses	X	X	X

Many of the studies in our sample make no specific mention of the impact of DPV on losses. Using information from those that do mention avoided losses and provide sufficient detail, we describe each method below and provide real-world examples, and we describe one additional method (marginal loss rate) that none of the studies appear to use. Table 15 compiles the methods used across the plans we reviewed.

Average loss rate: The simplest way to account for DPV's impact on losses is to scale the sales by a single average loss rate applied across all hours of the year to determine the load at the bulk power system level. Because DPV is removed from the load prior to the scaling up by the average loss rate, the planners implicitly account for the avoided losses of DPV based on the utility average losses, regardless of the correlation of DPV production and line loading. ELA, ISO-NE, LADWP, NVP, NSP, and NWPCC all specifically describe an average loss rate approach, though we expect this same approach is used by some utility planners who do not provide more detail in the planning documents.

Time-differentiated average loss rate: In a few cases, planning studies describe an approach for differentiating the loss rate based on the timing of the avoided losses. APS, for example, applies separate loss rates for each month to calculate load at the bulk power system level (Figure 18). APS also applies a separate capacity loss rate (11.7%, compared with 6.3% average energy

losses) to estimate the peak demand at the bulk power system level. APS accounts for the avoided energy losses of DPV by estimating the production of DPV in each month, and it includes the avoided capacity losses in its calculation of the capacity contribution of DPV.

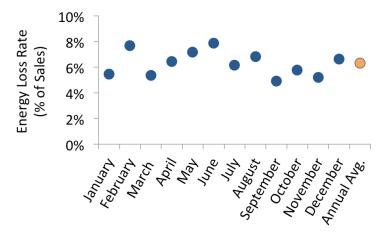


Figure 18. Example of Average Energy Loss Rate Differentiated By Month (APS)

GPC uses a value-of-solar analysis in its IRP to establish a ceiling for DPV bid prices, applying several loss categories related to DPV: reduced transmission losses (energy related), reduced transmission losses (capacity related), and reduced distribution losses (energy related). The energy-related reduced T&D losses are used to increase the avoided energy benefits of DPV. The capacity-related reduced transmission losses are used in the calculation of the deferred transmission capacity impact of DPV. GPC does not include a capacity-related component for reduced distribution losses, because it does not expect that DPV can defer distribution capacity investments.³⁸ The reduced distribution losses are estimated by weighting an hourly estimate of distribution losses by the hourly DPV profile. The hourly loss rates are not public.

PG&E uses assumptions provided by the CPUC in the Long Term Procurement Plan proceeding. The CPUC provides time-differentiated "peak" and "energy" loss rates for each of California's investor-owned utilities to apply to estimates of the avoided losses for any demand-side measures including DPV. For PG&E, the "peak" loss rate (9.7%) is nearly identical to the "energy" losses rate (9.6%), though there are bigger differences for SCE and SDG&E. The CPUC also differentiates between losses at the transmission level and distribution level.

Detailed analysis of losses: PSE does not address avoided losses in its evaluation of resource plans, but it does provide a supplementary, detailed analysis of the impact of high DPV penetrations on the distribution system. The analysis uses a detailed engineering model of four circuits with DPV penetrations that range from 9% to 135% of the circuit's peak load. PSE finds that losses increase with DPV on winter-peaking circuits with high DPV penetration, but losses are avoided with DPV on summer-peaking circuits with lower DPV penetration. It is not clear from the study description, but the study may assume that the distribution feeder cannot have

³⁸ GPC assumes that the distribution equipment must be sized to meet the full load on a distribution circuit, regardless of the DPV on a circuit, owing to current IEEE 1547 interconnection standards that require DPV to trip offline if the inverters sense low voltage on the grid and owing to the rapid decline in DPV production with clouds.

negative load (e.g., export power to the transmission system) and that any excess DPV generation is included in the losses.

Marginal loss rate: None of the studies appear to use the marginal loss rate when estimating avoided losses. Because losses increase non-linearly with line loading, a small decrease in load during high-load times can decrease losses by more than the average loss rate. To account for this benefit, one would use the marginal loss rate instead of the average loss rate. Lazar and Baldwin (2011), for example, use a rule of thumb that marginal losses are about 1.5 times average losses. This marginal loss rate could be time-averaged over the year, or it could be time-differentiated by hour, month, or "peak" versus "energy" as utilities have done with the average loss rates.

Table 15. Methods Used to Account for the Avoided Losses of DPV

Plan	Method	Details
APS 2014 IRP	Time- differentiated average loss rate	The average energy loss rate varies each month, with an average of 6.3% over the year. An avoided capacity loss rate (11.7%) is applied to the DPV capacity contribution.
ELA 2015 IRP	Average loss rate	DPV reduces demand, and load is grossed up to the system level based on average T&D losses.
GPC 2016 IRP	Time- differentiated average loss rate	Avoided cost calculations include avoided losses. They account for avoided energy and capacity losses at the transmission level and avoided energy at the distribution level.
ISO-NE 2015	Average loss rate	DPV reduces distribution losses at the average distribution loss rate of 5.5% of load.
LADWP	Average loss rate	Accounts for avoided energy losses.
NVP 2015 IRP	Average loss rate	Uses the average loss rate of 3.8% of sales to account for system peak net of DPV and avoided energy losses.
NSP 2015 IRP	Average loss rate	Uses the historical average loss rate for each jurisdiction.
NWPCC 7 th Power Plan	Average loss rate	The reduction in load from DPV is adjusted for transmission (assumed to be 2.3%) and distribution (assumed to be 4.7%) system losses.
PG&E 2014 BPP	Time- differentiated average loss rate	Avoided losses are based on average "peak" (9.7%) and "energy" (9.6%) loss rates.
PSE 2015 IRP	Detailed analysis of losses	PSE does not mention avoided losses in the evaluation of DPV as a portfolio option but does show a supplementary analysis of the impact of high penetrations of DPV on the distribution system. High DPV penetration can increase losses on winter peaking circuits and decrease losses on summer peaking circuits.

10. Considering Changes in Costs and Benefits of DPV with Higher Solar Penetration

Planner's question: How do you account for the fact that the benefits and impacts of DPV can change with higher levels of deployment?

As the penetration of PV increases on the grid, we expect the marginal value of additional PV to decrease (Lamont 2008, Mills and Wiser 2012a, Hirth 2013, Hirth 2015), as depicted in Figure 19. The primary drivers of this change are the declining capacity value (ability to avoid the need to build conventional capacity resources) and energy value (e.g., avoided fuel and purchased power costs) (Mills and Wiser 2012a). The capacity value decreases as the timing of the peak net load shifts from summer afternoons, when PV is generating significant amounts of power, to early evenings, when PV is off (Mills and Wiser 2012b, Muñoz and Mills 2015). The energy value decreases owing to additional PV displacing lower and lower variable-cost plants (like more efficient combined-cycle gas turbines or coal plants) and eventually requiring curtailment of excess PV production (Denholm and Margolis 2007, Denholm et al. 2009, Mills and Wiser 2012a, Denholm et al. 2016). In some cases, integration costs, avoided losses, and other factors might also depend on PV penetration. Where planners are considering potentially significant DPV penetrations, it may be important to account for these changes in value.

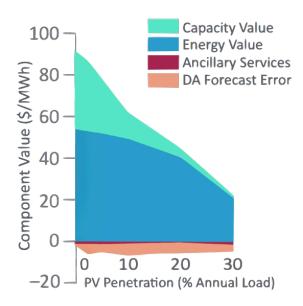


Figure 19. Estimate of PV's Declining Marginal Economic Value in California in 2030 with Increasing PV Penetration (Mills and Wiser 2012b)³⁹

In this section, we examine the approaches that utility planners use to account for changes in the costs and benefits of DPV with changing PV penetration. This is important both for market-driven DPV, in terms of identifying the remaining system need to meet the net load, and for DPV as a resource, in terms of comparing the benefits of DPV to its costs.

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³⁹ DA in the legend is an abbreviation for day-ahead.

Innovations in Accounting for Value Changes at High Solar Penetration

Perhaps because few utilities expect high penetrations of solar in the near future, innovative methods for addressing the value changes at such penetrations are lacking among the studies we evaluated. GPC's avoided cost of DPV calculations estimate the incremental avoided cost for tranches of DPV, illustrating a general approach to explicitly accounting for changes with increasing solar penetration, though some details are redacted. Many utilities employ production cost models, and these tools can be used to show changes with increasing solar penetration.

Though not mentioned in any study we evaluated, CEMs can also account for changes in the energy value with penetration, depending on the temporal resolution of the model. The capacity credit, on the other hand, is often specified exogenously to the CEM, which requires planners to specify a capacity credit that changes with penetration. Alternatively, CEMs could be structured to include an endogenous estimate of PV's capacity credit that reflects changes with penetration (e.g., Muñoz and Mills 2015).

One complicating factor is that the change in value with penetration may depend on other external factors (Mills and Wiser 2015). LADWP, for example, highlights that EV charging during the day may mitigate some of the challenges with overgeneration. Customer adoption of EVs and their preferences for charging the EVs may therefore affect the value of DPV at high penetration. Given uncertainty in how customer preferences and other factors may change over time, scenarios analysis and analysis of the robustness of decisions (see Section 4) may be helpful to decision makers.

Very few of the utility planning studies explicitly describe how they account for changes in the costs and benefits of DPV with increasing penetration. Many of the utilities, however, evaluate portfolios with DPV using a detailed hourly production cost model. If the utility includes both an hourly DPV generation shape and the hourly load shape, then the resulting production cost from the portfolio will reflect the potential changes in the avoided resources as DPV increases. Users of a detailed production cost model with hourly net load include APS (PROMOD), IPC (AURORA), LADWP (Prosym), NV Energy (PROMOD), and PSE (AURORA). LADWP highlights results from its production cost modeling with overgeneration during low-load spring days with high solar.

Only a few studies mention capacity credits for DPV that change with penetration level. ⁴⁰ NV Energy and PAC both use the peak hourly net load to set capacity requirements, which implicitly reflects a declining capacity value of DPV if the peak net load hours shift to early evening. APS and GPC both explicitly calculate capacity credits that depend on the solar penetration level. The declining incremental capacity credit with increasing penetration of DPV used by GPC is shown in Figure 20.

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⁴⁰ PNM (2014) also accounts for declining capacity contribution of PV with increasing penetration, but only for utility-scale plants included in the Strategist CEM.

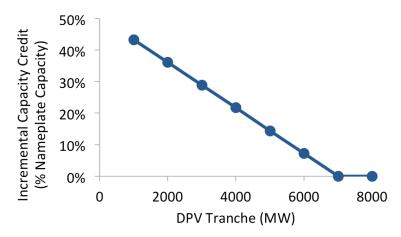


Figure 20. Incremental Capacity Credit of DPV for Each 1,000-MW DPV Tranche (GPC 2016)

Two utilities, DEC and IPC, include integration costs that depend on the level of PV penetration. The integration costs for DEC are derived from a study led by Pacific Northwest National Laboratory that examines three different PV deployment cases (Compliance, Mid, High). The study calculates the integration cost in different years between 2014 and 2022 for each deployment case, finding that integration costs increase in the Mid and High deployment cases and with time. For 2022, the integration costs in the Compliance case are about \$6/MWh (and PV capacity is about 5% of peak load), increasing to almost \$10/MWh in the High deployment case (PV capacity is about 19% of peak load). IPC similarly estimates an integration cost for increasing tranches of PV ranging from \$0.5/MWh to \$7.8/MWh depending on the tranche.

GPC calculates the avoided costs for incremental tranches of DPV. In this approach, all categories of avoided costs can vary with the tranche. Unfortunately, all of the avoided cost estimates are redacted from the publicly filed plan, and many of the formulas are also redacted. GPC appears to account for changes in avoided energy cost, avoided capacity cost, and avoided T&D. The avoided transmission is calculated by first establishing a baseline transmission plan without DPV, assuming a certain amount of load growth. GPC then increases DPV deployment in each tranche to determine if any of the baseline transmission projects could be deferred. The reduction in the present value of the cost with the deferral is then used as the basis for the avoided transmission cost for each tranche. GPC also includes three other categories of avoided costs that change with the tranche: a generation remix cost (related to a shift in the preferred conventional capacity to meet the net load), support capacity costs (related to flexible reserves and the integration costs discussed in other studies), and bottoming-out costs (related to curtailment of DPV starting at the 5,000-MW tranche).

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⁴¹ The factors included in the integration costs are described in more detail in Section 6. Here we only provide details regarding the changes in the integration costs with penetration.

None of the studies mention changes in avoided losses.⁴² Aside from GPC's study, other studies only mention changes in T&D costs with increasing penetration in qualitative terms or with respect to identifying the hosting capacity of feeders.

Text Box 4. Evaluating Bundled DPV Options

One commonly discussed option to enhance the value of DPV and prevent changes in value with high penetration is to bundle DPV with enabling technologies such as storage or load controls. In our review, we see mention of several utility pilots that would demonstrate DPV plus storage applications, TGT considers a grid-defection scenario in which customers use DPV plus storage to disconnect entirely, HECO considers a "no-export" scenario in its distribution planning in which customers with DPV would use storage or load control to prevent net exports from the home, and Navigant (2016a) evaluates the cost of increasing hosting capacity, including storage as an option. Aside from these scattered examples, however, most utilities consider only DPV, without bundling it with other technologies. Given the rapid increase in interest, utility planners may want to consider evaluating these bundled technologies in future planning studies, particularly where rapid DPV growth is expected.

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⁴² GPC has avoided cost of losses that changes with the tranche, but only due to changes in the avoided energy costs—the loss rates are independent of the tranche.

11. Integrating DPV in Planning across Generation, Transmission, and Distribution

Planner's question: How do you coordinate assumptions, scenarios, benefits, and impacts of DPV across generation, transmission, and distribution planning functions?

In most regions, the planning forums are isolated. Resource, transmission, and distribution planning are all conducted by different entities or functional groups within utilities. They may involve different regulators, they can have different objectives, and they have different time frames. In areas with growing shares of DPV, however, planning decisions cannot be made in isolation. For example, the need for generation resources depends on losses on the T&D system, which can, as described in previous sections of this report, change with the share of DPV. Similarly, the cost effectiveness of DPV as a resource depends on the impact of DPV on T&D investments. These challenges can be addressed through better coordination and integration of the different planning functions or forums (Sterling et al. 2015).

One way to achieve better coordination is to ensure that consistent scenarios, assumptions, and data are passed between different planning entities. The Long Term Procurement Planning process in California, for example, coordinates planning assumptions among the CEC, CPUC, and CAISO. Forecasts of customer DPV adoption developed by the CEC are used by the utilities in developing procurement plans and by CAISO. The CPUC also uses an RPS Calculator, which includes DPV as a resource, to develop portfolios of resources to include in planning studies by the utilities and CAISO. The recent DRPs by the California investor-owned utilities similarly build, in part, on a common DPV forecast from the CEC. Additional examples include the NYISO coordinating load and capacity assumptions through its annual "Gold Book." The 2015 Gold Book includes a base DPV forecast by load zone. Also, ISO-NE uses a regional system planning process to identify the region's electricity needs over a 10-year horizon, including a DPV forecast. ISO-NE uses the same DPV forecast in transmission planning and the capacity market, then shares the forecast with other regional planning entities for their planning process.

A second approach is to develop iterative planning practices that directly link the different planning forums. One example of this approach, illustrated in Figure 21, creates multiple flows of information between distribution and integrated resource planning. This proposal emerged from SMUD while assessing the impacts of growing shares of DPV. Key aspects of that information flow include forecasting DER adoption, both at the system level and feeder by feeder, and coupling distribution system impact modeling with bulk power system modeling. HECO recently implemented a similar process in its recent 2016 PSIP by linking several different models (including models of the distribution and bulk power system) and iterating between the models.

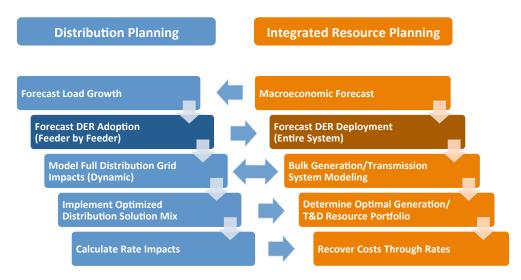


Figure 21. Proposal to Integrate Distribution and Resource Planning (Wilson et al. 2015)

One of the challenges to integrating different planning forums is the different levels of granularity. Distribution planning, for example, is very granular in terms of the location of individual elements in the grid, though it often focuses on conditions during peak load. Conversely, IRPs have very little locational granularity, but economic cost-effectiveness questions require assessments of costs across all hours of the year, projected at least 10–20 years into the future. A recent assessment of planning capabilities indicates that "distribution planning tools currently in use are not equipped to support the analysis of where and how DER systems can provide alternatives to traditional equipment and sources of supply" (EQL Energy 2015). However, emerging analysis platforms allow utilities to automate distribution planning analysis and integrate with transmission planning (e.g., EDD's DEW/ISM used by Pepco), conduct detailed bottom-up, location-specific value analysis of DER resources from detailed distribution plans and aggregate those values to be used in IRPs (e.g., Integral Analytics' LoadSEER used in PG&E's DRP), or more generally integrate several sources of utility data into a distribution planning framework (e.g., Qado's GridUnity used by SCE). These emerging tools help to more fully evaluate the impacts and benefits of DPV and other DER from the distribution system up. The key advances leveraged by several of these technologies are automated planning steps, advanced algorithms, and high-performance cloud computing. The rapid pace at which complex analysis can be done enables relatively quick analysis of "what-if" scenarios and evaluation of different assumptions. This can provide additional insight and increase the level of understanding for a broad set of stakeholders. Colman et al. (2016) provide additional background and uses of these emerging tools.

Beyond integration across planning forums, full consideration of DPV will require integration into procurement, programs, and pricing decisions. For example, DPV may affect the design of retail rates (e.g., NEM or time-of-use periods), which in turn impacts customer adoption of DPV and the need for other resources. DOM, for example, includes an analysis of alternative rate designs to estimate future loads. This is not connected to the DPV forecast, but in the future alternative rate designs could be a factor that impacts DPV deployment and planning needs.

12. Conclusions

The rapid growth of DPV has not been distributed equally across U.S. utility territories, and the same is true for projected future growth. While some of the studies we review forecast 2020 DPV penetrations equivalent to 5% or more of retail sales, fewer than half consider penetrations beyond 1% by 2020. Thus it is unsurprising that utilities and other planning organizations have differed in their perceptions about the need to incorporate DPV into resource and T&D plans. Because of this staggered progress, organizations that are just beginning to address DPV can draw on innovative practices from organizations that already are incorporating DPV rigorously into their plans. Our report reveals this spectrum of approaches across nine key planning areas, and it identifies areas where even the best current practices might be enhanced. Here we highlight approaches that are innovative and potentially worthy of emulation. We conclude with a brief discussion of future work.

Developing a Forecast of DPV Deployment

Customer-adoption modeling explicitly uses historical DPV deployment, location-specific DPV technical potential, various DPV economic considerations, and end-user behaviors as predictive factors. A quarter of the studies use this innovative method, including those by NWPCC, PAC, PG&E, PSE, and WECC. Though our analysis suggests various ways to improve current customer-adoption models, these models represent the most comprehensive forecasting approach available today. Our analysis suggests that combining various DPV forecasting methods could be valuable. Such an approach might use program goals discounted for uncertainty as lower bounds, customer-adoption models to forecast expected levels, and third-party forecasts and stipulated what-if scenarios to explore the full range of plausible futures. The customer-adoption models used in practice could be improved by better reflecting the heterogeneity of potential consumers, representing regional or locational differences, grounding methods in empirical data, and including non-economic factors.

Ensuring Robustness of Decisions to Uncertainty in DPV Quantity

Robustness of decisions to uncertainty in DPV adoption is most clearly addressed in utility integrated resource planning, with some consideration in transmission planning and little in distribution planning. The per-scenario plan method uses a CEM to develop least-cost plans that account for changes in both net load and the generation portfolio for various scenarios. An innovative variation of this approach—acquisition path analysis—combines multiple per-scenario plans with trigger events, which indicate when conditions have changed sufficiently from the expected to trigger modifications in resource-acquisition strategy. PAC and HECO use variations of this approach in their resource planning.

Characterizing DPV as a Resource Option

Fewer than half of the studies we review evaluate DPV as a resource that could be proactively deployed to meet future needs. Those that do consider DPV as a resource use various approaches to determine if it should be part of the plan. The two most common are to compare the performance of candidate portfolios with varying quantities of DPV and to develop minimum-cost portfolios via CEMs with DPV as a resource option. Regardless of the characterization method used, the ways DPV is distinguished from other resource options are important. Some utilities dismiss DPV based only on its higher cost and lower capacity factor relative to UPV. However, DPV's capacity credit as well as the avoided losses, transmission deferrals, and

distribution-system cost impact associated with DPV also can be significant. PG&E's plan stands alone among the utility resource plans we review in accounting for all these factors, which are also important for the locational net benefits methodology in the California DRPs and the NY REV process.

Incorporating the Non-Dispatchability of DPV into Planning Methods

Rather than a distinct innovative practice for incorporating the non-dispatchability of DPV in planning, innovation in this area is represented by evolving methods for capturing this important aspect of DPV. Hourly DPV generation profiles allow for some potential integration issues to be included when evaluating portfolios with DPV, including multi-hour ramping impacts and overgeneration. Most planning studies in our sample appear to use an hourly DPV profile. Impacts of DPV that are not captured with hourly generation profiles, such as sub-hourly variability and uncertainty, can be addressed through detailed integration studies. Various studies quantify the operational integration costs of solar, suggesting a range of \$0.5-\$10/MWh (for all solar, not just DPV). The methods used to estimate DPV's capacity credit vary and are not always described. A few utilities use detailed reliability-based models to estimate DPV's ELCC, whereas others use less-rigorous methods to estimate capacity credit. Among the other integration-related issues discussed in the studies, LADWP highlights the overgeneration potential of low-load spring days and considers mitigation via EV charging during these periods. Combining hourly DPV profiles with detailed production cost models can help in evaluating the role of EVs and other technologies and in identifying times when overgeneration may be a concern.

Accounting for Location-Specific Factors of DPV

Transmission and distribution planning studies require projections of DPV locations. The propensity-to-adopt method employs predictive factors such as demographics and customer load. Utilities that use this innovative analysis include PG&E, SCE, and SMUD. Another emerging utility innovation is locating DPV strategically to enhance its benefits. Organizations exploring this tactic generally focus on utility-owned systems, though other strategies have also been demonstrated in pilots. It is important to understand opportunities to strategically site DPV in planning, because location can affect the benefits of DPV (e.g., deferral of T&D upgrades) and the costs (e.g., incentives for DPV adoption in key locations).

Estimating the Impact of DPV on T&D Investments

Innovations in estimating the impact of DPV on T&D investments apply differently to different organizations, depending on each organization's current progress in this area as well as its projected DPV deployment and the robustness of its T&D infrastructure. For organizations that have not yet considered DPV in T&D studies, innovative examples of such planning are available from numerous planning entities. Likewise, organizations that find themselves needing to calculate hosting capacity—the amount of DPV that can be interconnected to the distribution system without violating operating limits—can draw on innovative studies from their peers. These include the use of hosting capacity analysis to both screen and steer the location of DPV. At the most advanced end of the spectrum, some organizations are already proactively planning investments to accommodate additional DPV. Innovative analyses by Pepco, DOM/Navigant, and HECO calculate the cost of various options for increasing hosting capacity, including the impacts of advanced inverters and energy storage.

Estimating the Avoided Losses Associated with DPV

Because of the non-linear variation of line losses with load, the most comprehensive estimation of system losses—and thus the potential avoided losses with DPV—is a time-differentiated marginal loss rate. However, none of the studies we evaluate appear to use a marginal loss calculation. This represents an area for future innovation. The one detailed circuit-level analysis of losses, by PSE, offers a different refinement at a relatively small scale.

Considering Changes in Costs and Benefits of DPV with Higher Solar Penetration

Perhaps because few utilities expect high penetrations of solar in the near future, innovative methods for addressing the value changes at such penetrations are lacking among the studies we evaluate. GPC's avoided cost of DPV calculations estimate the incremental avoided cost for tranches of DPV, though some details are redacted. Many utilities employ production cost models, and these tools can be used to show changes with increasing solar penetration. CEMs could also account for changes in the costs and benefits of DPV with penetration, though modifications to the models might be necessary. In addition, none of the studies mention changes in avoided losses with higher solar penetration.

One complicating factor is that the change in value with penetration may depend on other external factors. LADWP, for example, highlights that EV charging during the day may mitigate some of the challenges with overgeneration. Customer adoption of EVs and their preferences for charging the EVs may therefore affect the value of DPV at high penetration. Given uncertainty in how customer preferences and other factors may change over time, scenarios analysis and analysis of the robustness of decisions may be helpful to decision makers.

Integrating DPV in Planning across Generation, Transmission, and Distribution

Fully integrating DPV into planning requires a more comprehensive approach in which distribution, transmission, and resource planning are more tightly linked. A few states and regions—including California, New York, and New England—have started to develop these more comprehensive processes, but there are still many issues to address. Understanding the range of different approaches across the United States and highlighting innovative practices should help accelerate those changes.

Future Research

With future research, we will analyze whether some of the innovative practices identified here can meaningfully affect planning study results. Of particular interest are innovative practices for forecasting DPV adoption, examining the robustness of decisions to DPV uncertainty, and considering DPV as a resource.

More generally, planners could improve the representation and evaluation of DPV bundled with other enabling technologies such as storage and load control across multiple methodological areas. These include forecasting, consideration as a resource option, assessing the impacts to the T&D system, and understanding the impacts of bundled DPV at high solar penetration levels.

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Appendix A. Documents Used in Planning Study Review

Resource Plans

Arizona Public Service (APS) 2014 Integrated Resource Plan

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Appendix E: Renewable Energy

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Appendix I: Forecast Methodology

https://www.xcelenergy.com/staticfiles/xe/PDF/Regulatory/12-App-I-Forecast-Methodology-January-2015.pdf

Appendix J: Strategist Modeling and Outputs

https://www.xcelenergy.com/staticfiles/xe/PDF/Regulatory/13-App-J-Strategist-Model-Description-and-Methodology-January-2015.pdf

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Appendix E: Demand Forecast

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Appendix B. Forecasts of DPV Penetration

We contrast the DPV electricity-penetration forecasts in long-term planning documents from 19 utilities and two ISOs to forecasts from two solar industry sources (BNEF and GTM Research) and results of NREL's dSolar model. DPV penetration is defined as the ratio of annual DPV electricity generation to annual utility sales, after accounting for energy savings from EE programs, demand response programs, and customer-sited generation such as DPV. Such a metric allows us to easily compare DPV growth among utilities of various sizes in terms of customer base, annual energy consumption, and geographic footprint. Where possible, we extract both the DPV generation and the utility sales directly from consistent scenarios in the long-term planning documents. In some cases, not all numbers are explicitly provided, so we estimate the figures using the methodology described below.

DPV Forecasts

In the planning documents, the cumulative DPV capacity for a given year is calculated based on annual DPV capacity additions and known base quantities for prior years as listed in the IRPs. If capacity is listed in AC terms, we convert it into DC terms with a standard DC-AC derate factor of 0.88 (similar to the standard assumptions in the PVWatts model).

We combine the GTM Research and BNEF annual state-level residential and commercial PV capacity estimates and supplement them with state-level cumulative DPV capacity information for the year 2010. Neither GTM Research nor BNEF provide capacity projections out to 2030, so we do not include them in our long-term comparison. For both GTM Research and BNEF, we differentiate between estimates that include extension of the solar ITC until 2022 and those that assume it expires at the end of 2016. BNEF explicitly creates scenarios with and without the ITC extension, holding all other factors constant (BNEF 2015). The GTM Research/SEIA DPV forecasts from early 2015 were developed prior to the ITC extension, while those from early 2016 were developed after the ITC extension. We include the 2015 and 2016 forecasts but note that they also incorporate other policy and market changes that occurred between the two forecasts (GTM Research and SEIA 2015, GTM Research and SEIA 2016).

We use a range of scenarios from NREL's dSolar modeling results for near- and long-term DPV capacity projections in Section 3.4 (Gagnon and Sigrin 2016). All scenarios include the 2016 ITC extension, which differs from the assumptions in most of the utility forecasts. The dSolar Reference Scenario is based on NREL's Annual Technology Baseline Midcase Cost Scenario. The SunShot Cost Scenario assumes achieving SunShot cost targets for residential and commercial installations by 2020 without any further cost reductions in years to follow. The Low Cost Scenario also assumes meeting SunShot cost targets in 2020, but it includes further price declines until 2030. The \$10 Carbon Scenario assumes Reference Scenario project prices and an additional \$10 per metric ton of CO₂ emissions that increases electricity rates and thus makes the customer economics of DPV more attractive. The scenarios do not otherwise differ in assumptions about electricity price changes (escalate following EIA AEO projections) or NEM policies (based on current state laws).

Across all forecasts, we estimate annual DPV electricity generation using a statewide rooftop capacity factor derived from Lopez et al. (2012, Table 4) and the forecasted DC capacity of

DPV. We use estimates by Piwko et al. (2012) for Hawaii. Where the utility service territory covers multiple states, we use a capacity-weighted average capacity factor.

Utility Sales

We extract sales forecasts for the utility planning studies from the original planning documents. To develop load forecasts used to calculate forecasted industry and dSolar DPV penetrations, we start with the most recent state-level retail-sales information from EIA Form-861 and then apply annual load-growth rates implicit in EIA's 2015 Annual Electricity Outlook (EIA 2015).

Comparison of DPV Penetration

Because our third-party DPV forecasts are available only at the state level, and not at the service-territory level, we compare utility DPV estimates with third-party forecasts for the same state, though we recognize that utility service territories may differ in terms of solar resource quality and customer economics from the statewide average. As a result, third-party DPV estimates are the same for utilities in the same state. For example, the third-party estimates for TEP and APS both use the state-level forecasts for Arizona. Where a utility is active in more than one state, a utility-specific load-weighted average is calculated from the state-level third-party estimates. PAC's load, for example, is split with 44% of load in Utah, 23% in Oregon, 17% in Wyoming, 7% in Washington, 6% in Idaho, and 1% in California.