BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

In the Matter of a Working Case	)	
to Explore Emerging Issues in	)	**File No. EW-2017-0245**
Utility Regulation	)	

PUBLIC COUNSEL'S COMMENTS ON DRAFT RULE, 4 CSR 240-22.055

Public Counsel requests that the Commission consider Public Counsel's comment recommending that the draft rule is not necessary for the reasons set forth in the attachments hereto. These comments build off the original comments filed on June 8.2018.

Public Counsel's attachments consist of a memorandum and two academic, peer-reviewed articles regarding distribution system impacts of solar PV on California's grid.

WHEREFORE, Public Counsel requests that the Commission consider Public Counsel's comment recommending that the draft rule is not necessary for the reasons set forth in the attachments hereto.

Respectfully submitted,

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ATTORNEY FOR THE OFFICE
OF THE PUBLIC COUNSEL

CERTIFICATE OF SERVICE

The undersigned certifies that a true and correct copy of the foregoing document was sent by electronic mail or by U.S. Mail, postage prepaid, on July 16, 2018 to all counsel of record.

/s/ Ryan D. Smith

MEMORANDUM

To: Missouri Public Service Commission Official Case File,
Case No. EW-2017-0245

From: Geoff Marke, Chief Economist
Missouri Office of the Public Counsel

Subject: RE: Draft Rule Comment, 4 CSR 240-22.055

Date: July 16, 2018

General Comments:

OPC appreciates the opportunity to again file comments to the Commission's Staff regarding the Staff's redlined submitted draft Distributed Energy Resource ("DER") Analysis rules put forward as possible additions to the Commission's existing Chapter 22: Integrated Resource Planning ("IRP") rules.

OPC's continues to maintain the position that these specific rules are not necessary, and, as drafted, the proposed additions will not produce the desired outcome the Commission is likely seeking. In this regard, OPC does not believe the current regulatory and policy environment necessitates such action and has serious concerns that the opportunity cost in time, money and energy spent on performing the recommended analyses will outweigh the benefits.

Re-drafted Rule Comments:

Regarding the re-draft language provided by Staff, OPC would like to specifically comment on the proposed inclusion of a new cost-effective threshold proposed by Staff which states:

> (B) Cost-effective means that a resource passes one of the standard cost-effectiveness tests prescribed in the National Standard Practice Manual published by the National Efficiency Screening Project (NESP):

It is not entirely clear what Staff means here. The aforementioned manual does not endorse any specific tests but rather provides a resource value framework, with many possible inputs. Admittedly, the inputs utilized in any cost-effective screening are rarely agreed on by stakeholders; however, the rule as presently drafted merely compounds the uncertainty surrounding valuation.

OPC would welcome further discussions surrounding an appropriate framework that could lead to agreed-on inputs. Or even why such a framework is necessary. Such deliberations should precede the submission of the draft rules to the Secretary of State's Office. Without further refinement, the uncertainty around this definition will likely magnify disagreements amongst stakeholders by increasing the amount of categories in which secondary and tertiary "costs" or "benefits" are supposed to be relied on. For example, there would be endless opportunity for "gaming" of data from all stakeholders as many of the inputs in the framework are subjective, interdependent with other inputs, or subject to double-counting. The inclusion of this language will provide greater uncertainty, not less, and should be deleted in total.

For the Commissions Consideration:

OPC has attached two academic, peer-reviewed articles regarding distribution system impacts of solar PV on California's grid for consideration and discussion. Both studies, published in 2016, are based on data provided by *Solar City* and *PG&E*. The studies find that rooftop solar does help the distribution system, but that the magnitude of the benefits are very small. As summarized by Lucas Davis of the Haas Energy Institute, University of California, Berkeley (and paraphrased by this author):

- The capacity benefits are small for most cases. Less than 0.2 cents per kWh and will shrink over time. For perspective, in California, the typical wholesale electricity prices are about 4.0 cents kWh, and average retail prices are 19.0 cents per kWh.

- There is a reduction in energy losses with some as high as 30% in areas of very high penetration levels. However, these gains are small in absolute terms, representing less than 5% in the distribution system, or less than 0.2 cents per kWh in overall benefits.

- There were limited reductions in transformer aging, with a small number of examples in which rooftop solar significantly increased transformer aging, driven by a surge of power back to the grid in places with large amounts of solar were present.

- There were large benefits (x 10 the average capacity benefit) in certain specific locations (top 1%) for circuits very close to needing a capacity upgrade. Which suggests that location can matter; however, the authors make a point in noting that no policy is currently in place that allows for this kind of highly-granular pricing of rooftop solar benefits (as is true for Missouri as well).[1]

OPC provides the aforementioned information to illustrate that when distribution system benefits of rooftop solar are quantified, they are too small to be used as an argument to favor rooftop solar over grid-scale renewables. Perhaps more importantly, there is no statute mandating that customer-owned DERs adhere to a locational requirement. Rooftop solar vendors operate in the free market and not under a command-and-control bureaucracy.

Stated differently, for most customers, whether or not they choose to invest in a DER is almost entirely dependent on the costs and benefits to them personally, not the costs and benefits to the distribution system. Net metering benefits all rooftop solar adopters—including those in the 1% of high-value locations and the other 99%.

[1] Davis, L. (2018) Does rooftop solar help the distribution system? Energy Institute/ Haas-Berkeley https://energyathaas.wordpress.com/2018/06/25/does-rooftop-solar-help-the-distribution-system/

Again, OPC suggests that further discussion is warranted as to the intent of including the rules as presently drafted. What is to be gained from ratepayers paying for a database to track customer-owned DERs? By the time, such a database would be operational, most of the allocated money carved out for rebates from SB 564 would likely be spent down.

As drafted, at least for today and the foreseeable near future, it would appear this exercise would merely show that most customer-owned rooftop solar, on a whole, provides little or no benefit to the distribution system.

BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

AFFIDAVIT OF GEOFF MARKE

STATE OF MISSOURI)
) SS.
COUNTY OF COLE)

COMES NOW GEOFF MARKE and on his oath declares that he is of sound mind and lawful age; that he contributed to the foregoing *Proposed DER Rules;* and that the same is true and correct according to his best knowledge and belief.

Further the Affiant sayeth not.

Geoff Marke
Chief Economist

JURAT

Subscribed and sworn before me, a duly constituted and authorized Notary Public, in and for the County of Cole, State of Missouri, at my office in Jefferson City, on this 16th day July 2018.

NOTARY PUBLIC NOTARY SEAL STATE OF MISSOURI

JERENE A. BUCKMAN
My Commission Expires
August 23, 2021
Cole County
Commission #13754037

Jerene A. Buckman
Notary Public

My Commission expires August 23, 2021.

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Effects of distributed PV generation on California's distribution system, part 2: Economic analysis

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Abstract

The economic value of distributed photovoltaic (PV) electricity is affected both by its correlation with transmission level energy prices and by a host of effects it may have on distribution systems. In this study we combine detailed physical simulation of distribution circuits with budgetary information provided by Pacific Gas & Electric (PG&E) to estimate PV's value with respect to avoided wholesale energy expenditures, avoided distribution system capacity upgrades, and increased expenditures to manage voltage magnitudes. We find that favorable timing of generation and the potential to defer capacity investments both increase PV's value on average by a small amount. We use circuit-level loading and load growth data to show that distribution circuit capacity value is very heterogeneous: PV shows very little capacity value on most circuits but substantial (over $60/kW-year, nearly half of the near-term target for the cost of distributed PV) on 1% of circuits at low penetrations. We examine some other distribution system impacts of PV, including voltage regulator operations and voltage quality, and find that they are also likely to be very small on average, with the caveat that there are some impacts (such as the effect of reverse power flow on protection equipment) that we have insufficient data to assess. In much the same way that dynamic pricing tariffs capture PV's value in time, our results point toward the importance of tariffs that recognize the heterogeneity of PV's impacts on distribution systems across different locations.

Keywords: Electric distribution; Photovoltaic generation; Valuation

1. Introduction

Distribution systems were designed to deliver power from high voltage transmission networks to customers. When photovoltaics (PV) are embedded in distribution systems, they fundamentally change power flow conditions: power transfer could go from one customer to another, or from customers back to the transmission system. This has created concern among distribution engineers, regulators and researchers as to whether distribution systems will be able to accommodate very high penetrations of PV – and if so, what the associated costs will be. There are a number of areas where PV could have important impacts, including: resistive losses, peak load (which impacts distribution capacity investments), and voltage levels at the point of utilization, transformer aging, voltage regulator mechanical wear, and the ability of protection systems to properly identify fault conditions.

A number of studies quantify various engineering impacts of PV in distribution systems (e.g. Quezada et al., 2006; Shugar, 1990; Woyte et al., 2006; Thomson and Infield, 2007; Navarro et al., 2013; Widén et al.,

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2010; Paatero and Lund, 2007; Hoke et al., 2013; Cohen and Callaway, 2013), but relatively little research has been done to translate the full range of engineering impacts into economic values. Indeed, the California Public Utilities Commission (CPUC) rejected the possibility of valuing PV's non-energy economic impacts, especially its possible deferral of generation, transmission and distribution capacity, on the basis of limited evidence (California Public Utilities Commission, 2011, p. 34). On the other hand, at CPUC's order, California's regulated utilities have recently filed "Distribution Resource Plans" outlining strategies to identify the hosting capacity of distribution circuits in each utility's service area (e.g. PG&E (2015)). However we are unaware of any available utility-wide analyses of the economic impacts that PV could have on distribution systems. This paper aims to fill this gap.

This is the second paper in a two-part series that quantifies the physical impacts of PV in distribution systems (Part 1, Cohen and Callaway, 2016) and applies those physical results to an economic framework that quantifies distributed PV's impact on distribution system operation and maintenance costs (Part 2, this paper). We assess these costs using a combination of (1) assumptions about growth in demand and PV capacity, and their interactions with one another, (2) a model of how PV capacity defers investment in distribution capacity infrastructure and (3) a unique set of data on distribution capacity expenditures and feeder-level growth rates from Pacific Gas and Electric (PG&E).

Our key findings are as follows: First, PV provides distribution circuit capacity deferral value of up to \$6/kW-year (using an annuity factor of 13.95, see Section 3.2.4.2) when averaged across the potential impact on *all* feeders in PG&E service territory. This is a very small fraction of the installed cost of PV (with a 13.95 annuity factor, approximately \$380/kW-year using historical cost estimates, or \$110/kW-year if near-term Department of Energy projections are met). However roughly 90% of these feeders receive no distribution capacity upgrade benefit from PV because their peak load is much less than their peak MW (or MVA) capacity or their load growth is low. We find that PV's capacity value (i.e. its ability to defer distribution system capacity upgrades) on the remaining 10% of feeders ranges from \$10/kW-year to more than \$60/kW-year at very low penetrations. This range suggests that the value on some circuits could be a significant fraction of the installed cost of PV. We also find that these benefits decline relatively quickly as additional PV is installed on each circuit; at 50% penetration, capacity value is halved relative to low penetrations.

Second, based on our engineering simulations of PV impacts on distribution circuits, we find PV's impacts on voltage magnitudes and voltage regulator operations are relatively small (Cohen and Callaway, 2013, 2016). If we assume that voltage regulator maintenance scales linearly with the frequency of operation, results in this paper indicate that distributed PV would increase PG&E's annual costs by \$442,000 if *all* circuits in PG&E territory had 100% PV penetration – an extremely small amount of PG&E's roughly \$6 billion operations and maintenance budget. Though we do not have circuit-level data to quantify the heterogeneity of the cost to address voltage issues, our earlier engineering simulations showed feeder location and design can significantly impact the likelihood that PV will create voltage problems, suggesting that proactive distribution planning may enable utilities to prevent these voltage problems before they occur.

1.1. Overview of PV economics

The first component of distributed PV's value is avoided costs of energy production from other generators. The second has to do with PV's impact on the performance and requirements of generation, transmission and distribution infrastructure. At the distribution level these impacts can be both positive and negative, including reducing line losses, avoiding the need to build distribution system capacity and also increasing voltage regulation problems. Third, PV reduces pollution and possibly other negative externalities associated with conventional generation. We also note that incentives for PV capacity may have *positive* externalities; incentivizing deployment might lead to otherwise unattainable economies of scale and technology learning.

Ideally, the price paid to PV owners would include accurate assessments of all of the above components of PV's value. Unfortunately, the second and third components are difficult to measure or estimate, and this uncertainty leads to controversy over the appropriate magnitude of incentives. This paper addresses these uncertainties by providing new estimates of the value of PV's energy and its effects on distribution systems.

Our analysis relies on simulated distribution system impacts. The advantage of this approach is that we can study high levels of PV penetration while taking into account important factors such as the smoothing of aggregate generation profiles due to small-scale geographic diversity of PV production. It also allows us to examine effects that cannot be addressed without a physical model, such as voltage quality. On the other hand, the detailed nature of the simulations limits our scope – in this case to one utility's territory, to a small but representative set of engineering models of distribution systems, and to one year of PV production and weather data.

1.2. Prior studies on system-level economics of PV

Three recent studies have examined how PV deployment might affect distribution capacity upgrades in California: Darghouth et al. (2010), Energy and Environmental Economics (2013), and Beach and McGuire (2013). Darghouth et al. (2010) used existing estimates of PV's transmission and distribution capacity value (i.e. its ability to defer T&D capacity upgrade investments) but noted that capacity value is highly uncertain (ranging from 0.1 ¢/

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kW h to 10 ¢/kW h). They also noted that accounting for avoided line losses increases the value of PV above wholesale generation costs, though not by a significant amount (Darghouth et al., 2010, pp. 40–42). The Crossborder Energy study (Beach and McGuire, 2013) allocates capacity credit (i.e. production in peak conditions) to distributed PV by examining its output during the hottest hours of the year, which generally correspond roughly to the hours with the most energy usage. These capacity credit allocations are multiplied by an estimated marginal cost of T&D capacity from utility rate cases to find a total capacity value (Beach and McGuire, 2013, pp. 23–28 of appendix B-2). E3 (Energy and Environmental Economics, 2013) uses a more granular method that estimates distribution capacity upgrade costs from specific projects forecasted by PG&E. They estimate the present value of PV for deferring those distribution capacity projects by crediting PV production in any hour that a generic substation load profile is within one standard deviation of its peak (Energy and Environmental Economics, 2013, pp. C-40–C-44). None of these studies investigate the distribution capacity value of PV at the circuit level and for different quantities of PV installed on each circuit.

In addition to these California-based studies, we are aware of a several other studies that address the economic impacts of distributed PV on distribution systems. These address the value of deferred distribution capacity upgrades and to a lesser degree avoided energy purchases (Woo et al., 1994; Gil and Joos, 2006, 2008; Piccolo and Siano, 2009).

This paper builds on prior work in several important ways. First, by working with circuit-level load growth assessments for each of PG&E's 3000 feeders, we investigate the full range of distribution capacity benefits on a feeder-by-feeder basis. Second, because we build our economic assessments up from a power flow model that uses real PV production data as inputs, we can assess the economics of other engineering impacts of PV in distribution systems (most notably voltage impacts). Third, we investigate the impacts of PV on distribution circuits at a large range of penetrations (PV capacity ranging from 7.5% to 100% of feeder peak demand); this allows us to quantify the declining distribution capacity benefits of PV as circuit-level net load peaks get pushed later in the day when PV production is low.

2. Simulation and utility data inputs

In this section we summarize the most relevant aspects of our study region and data inputs. We include a more detailed summary of the methods, as well as a summary of the results of the physical simulations, in the appendix. Part 1 of this two-part paper describes the physical simulation results in detail.

Our study focuses on climate, photovoltaic production and infrastructure representative of PG&E's territory (Northern California). PG&E accounted for 38.3% of California's total energy consumption in 2012 (California Energy Commission, 2013). We ran simulations over the 366 days between September 25, 2011 and September 24, 2012, inclusive. In this paper we focus on results for Berkeley and Sacramento, because they are representative of PG&E's two major climate regions (coastal and interior, respectively). We used production data from approximately 200 distributed PV systems in the study regions. We define PV "penetration" as the ratio of installed PV capacity to peak demand in the baseline (no PV) case. Due to variation in load shape and PV capacity factor across feeders and locations, energy penetration ranges from 0.3 to 0.6 times the PV capacity penetration across our study regions. See the appendices for this paper and Cohen and Callaway (2016) for additional detail.

We studied feeders using a simulation tool developed by Pacific Northwest National Laboratories (PNNL) called GridLAB-D (PNNL, 2012). The specific feeders we studied in come from a set of "taxonomy" models provided by PNNL. PNNL assembled the taxonomy set by first collecting 575 feeder models from a range of investor- and municipally-owned utilities and rural cooperatives in the United States (Schneider et al., 2008). PNNL then identified a set of 23 taxonomy models from the set of 575 via a systematic clustering analysis. In this paper we focus on taxonomy feeders associated with PG&E climate zones: five feeders in region 1 (R1, temperate west coast) and three in region 3 (R3, desert southwest). Though the original PNNL sample was neither random nor exhaustive, these feeders allow us to explore a broad range of PV's potential impacts. See Table 1 for a summary of the feeders.

2.1. Deployment timelines and financial discounting

We compute the net present cost or value of PV installed over a ten year horizon[1] using 2012 dollars, discounting with PG&E's weighted average cost of capital (WACC) of 7.6% less a combined inflation plus project escalation rate of 2.5% (PG&E, 2013a), yielding a net discount rate of $r = 5.1\%$.

We define penetration as follows:

$$p(t) = \frac{e^{\alpha t} - 1}{e^{\alpha T} - 1} X$$

where $0 < p(t) < 1$ is the penetration in year t, X is the final penetration and T is the year in which to reach the target penetration (ten, in our case). Fig. 1 illustrates how $p(t)$ depends on the shape parameter α. $\alpha \leqslant 0.4$ is likely the most reasonable range (with installations spread out over ten years), but we present results for $0 < \alpha < 1$ for comparison. When $p(t)$ did not correspond exactly to penetration levels that we modeled in GridLAB-D, we interpolated linearly between the two nearest penetrations that we had modeled.

[1] Although we only look at 10 years of PV deployment, we account for the value of capacity deferral for 25 years, see Section 3.2.

Table 1
Summary of simulated feeder characteristics.

Name[a]	Serves[b]	Nominal peak load (MW)[b]	Dist. transformers	Percent residential (%)	Approx length (km)	Baseline peak load (MW)		PV profiles selected for use	
						Berk.	Sac.	Berk.	Sac.
R1-12.47-1	Mod. suburban and rural	7.15	618	93	5.5	5.56	7.59	21	26
R1-12.47-2	Mod. suburban and lt. rural	2.83	264	84	10.3	2.00	2.82	30	30
R1-12.47-3	Moderate urban	1.35	22	13	1.9	1.27	1.60	10	8
R1-12.47-4	Heavy suburban	5.30	50	57	2.3	4.31	5.65	12	12
R1-25.00-1	Light rural	2.10	115	2	52.5	2.35	3.00	28	30
R3-12.47-1	Heavy urban	8.40	472	32	4.0	6.64	8.70	20	25
R3-12.47-2	Moderate urban	4.30	62	0	5.7	3.45	4.40	13	18
R3-12.47-3	Heavy suburban	7.80	1733	84	10.4	7.54	9.67	56	55

Nominal voltage is designated by 12.47 or 25.00 (kV).
[a] Climate region of origin is indicated by $R1$ (temperate west coast) or $R3$ (arid southwest).
[b] Schneider et al. (2008).

2.2. PG&E feeder data

We obtained feeder-level capacity and peak loading data from 2012 and projected annual load growth percentages for 2013–2017 for 2987 feeders in the PG&E service territory under the terms of a non-disclosure agreement (PG&E, 2013a). PG&E classifies feeders in two major regions: coastal (36.3% of all feeders) and interior (63.7%). We used peak demand projections (based on one-year-in-two weather data) provided directly by PG&E.

3. Economic results

3.1. Energy and transmission value of PV

PV's energy and transmission value is increased by PV production's positive correlation with electricity prices, and its tendency to reduce system losses.[2] Furthermore, to the extent PV causes distribution voltage magnitudes to change, voltage-dependent loads will change their consumption and this could increase or reduce energy expenditures. In this paper we quantify the combined economic effect of these factors with locational marginal prices (LMPs). Because LMPs include energy, transmission congestion and transmission loss components, they implicitly capture both the energy and transmission value of PV at specific locations.

We calculated the net locational marginal price (LMP) benefit for each feeder as the difference between the cost to supply energy at the substation at 0% PV penetration and the cost to serve the substation at the given PV penetration:

$$\begin{aligned} C_j(X) &= (\text{feeder } j \text{ energy cost without PV}) \\ &\quad - (\text{feeder } j \text{ energy cost with } X\% \text{ PV}) \\ &= \sum_t \lambda_{j,t} D_{j,t}(0) - \lambda_{j,t} D_{j,t}(X) \end{aligned} \tag{1}$$

where j indexes the taxonomy feeder, D is simulated hourly demand at the feeder head, and $\lambda_{j,t}$ is the hourly LMP for the feeder's location. Because LMP patterns will very likely change over ten years, depending on fuel and carbon prices and generation infrastructure – including solar generation, which will tend to suppress prices when solar radiation is high – the results we present here should be extrapolated into the future with caution. We obtained hourly LMPs from the California Independent System Operator's (CAISO) day-ahead market for nodes CLARMNT_1_N001 (Berkeley locations) and WSCRMNO_1_N004 (Sacramento locations) (CAISO, 2013a). We compared several nodes in the general area of Berkeley and Sacramento and chose these two arbitrarily after confirming that differences in price relative to neighboring nodes were very small.

We calculated a weighted average energy benefit within and across regions as follows:

$$C_{\text{av}}(X) = p_{R1} \sum_{j \in R1} f_j C_j(X) + p_{R3} \sum_{j \in R3} f_j C_j(X), \tag{2}$$

where X denotes the penetration level, R denotes region ($R1$, coastal; $R3$, interior), j indexes the taxonomy feeders, f_j denotes the frequency of feeders within each region (see Table A.2), and we used $p_{R1} = 0.363$ and $p_{R3} = 0.637$ to define the frequency of feeders in PG&E's coastal and interior zones, respectively (see Section 2). This provides a representative estimate of the energy benefit across all penetration levels. We computed PV energy for the representative sample, $E_{\text{PV,av}}(X)$ in the same way.

Next, we calculated the ratio of PG&E consumption to that in our sample (see Appendix C.1) denoted s_y with y indexing years. The ratio ranged from $s_1 = 5720$ to $s_{10} = 6453$.[3] Then, using the same method as in PG&E (2011), we levelized the energy benefits by dividing the

[2] Additional details on resistive loss reductions are available in Part 1 of this series (Cohen and Callaway, 2016).

[3] While the calculated multiplier was on the order of 6000, there are approximately 3000 feeders in PG&E's system. This implies that the average PG&E feeder uses about twice as much energy annually as our weighted average simulated feeder. Since the sample is being scaled to the full system size this discrepancy does not affect the overall magnitude of the results.

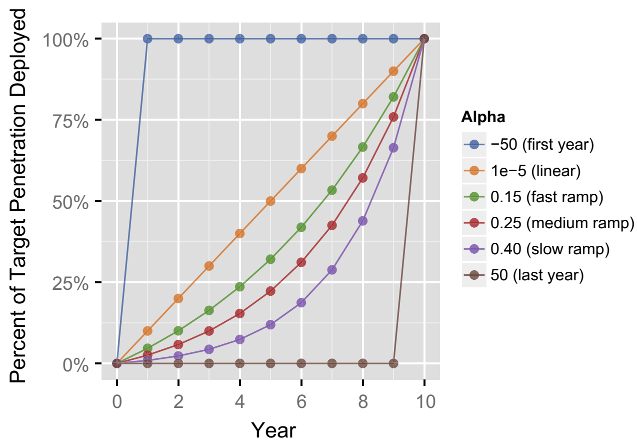

Fig. 1. Representative realizations of our deployment ramp up function $p(t)$ for varying α.

net present value of C_{av} by the sum of discounted PV generation, $E_{PV,av}$:

$$\text{Levelized Avoided Cost of Energy} = \frac{\sum_{y=1}^{10} \frac{s_y C_{av}(X_y)}{(1+r)^y}}{\sum_{y=1}^{10} \frac{s_y E_{PV,av}(X_y)}{(1+r)^y}} \quad (3)$$

For all locations, feeders, penetration levels and deployment rates we found the average levelized energy value to be between \$0.0349/kW h and \$0.0351/kW h. The small variation across scenarios was due to random variations in which PV generation profiles were chosen and where they were placed on the feeders (see Section 2). The weighted average LMP between Berkeley and Sacramento during our test year was \$0.0297/kW h,[4] meaning PV was about 18% more valuable than a resource with constant production and no effect on losses or voltage-dependent loads. This percentage is consistent with prior work, e.g. Borenstein (2008).

3.2. Distribution capacity value of PV

If PV reduces peak net load, it could defer investments in higher capacity distribution equipment such as transformer banks and conductors; this section seeks to quantify this deferral value.

3.2.1. Projects and feeder data

We compute distribution capacity benefit with an approach similar to Gil and Joos (2006), Piccolo and Siano (2009), Energy and Environmental Economics (2013), and Woo et al. (1994) and depicted in Fig. 2. We first establish a baseline estimate of the year in which distribution capacity projects would occur in the next ten years. Then, based on simulation results, we compute the year in which the same project would occur in the presence of PV. We continued to account for the cost of deferred projects for 25 years and considered projects deferred beyond 25 years to be completely avoided. Using a WACC of 7.6% (our nominal case), a project deferred from year 1 to year 25 would decrease in present cost by 71%.

We used feeder-level MW capacity and peak loading data for 2012–2017 (Section 2), and carried the 2017 growth rates forward for a rough prediction of future trends. We assumed each feeder project occurs in the year its peak load reaches 100% of rated MW capacity. In practice, other factors can affect project timing; see Section 3.2.5 for further discussion.

We eliminated the following categories from our analysis:

- Feeders operating at or below 4.16 kV (2.4% of PG&E MW capacity). These are smaller, older, idiosyncratic feeders that PG&E engineers felt would be inappropriate to include in this general analysis (PG&E, 2013a).
- Feeders exceeding 10% PV penetration (7.6% of PG&E MW capacity). Because peak load growth forecasts for these feeders are likely affected by existing PV, their forecasted growth rates do not provide a good "control" against which to apply further peak load reductions due to PV. These feeders are relatively similar to the population (2012 peak demand average of 7.0 MW versus 7.7 MW for the population; average voltage of 14.5 kV versus 14.1 kV for the population; and 31.4% coastal/68.6% interior versus 36.3%/63.7% for the population).
- Feeders already loaded over their rated MW capacity (1.7% of total capacity).

We used demand growth data to estimate which of the remaining feeders would require a capacity upgrade project within ten years. This left 296 feeders (roughly 10% of the 2987 feeders, and 20% of the total 20,600 MW of capacity, for which we received data). At roughly 30 projects per

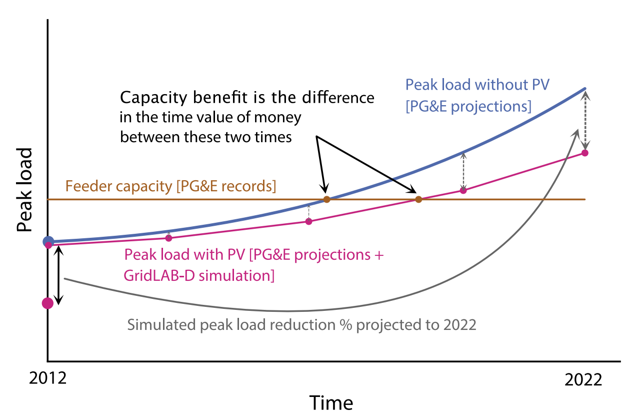

Fig. 2. Schematic showing how the value of distribution capacity investment deferral is calculated for an individual feeder at a given PV penetration.

[4] \$0.0297/kW h is roughly half the levelized cost of energy from combined cycle gas fired generators (U.S. Energy Information Administration, 2014), suggesting that the market is not in long-run equilibrium. This is likely because natural gas prices in the U.S. in late 2011 and 2012 were extremely low. But it may also reflect the fact that a portion of generators' levelized costs are paid for via resource adequacy capacity contracts. This highlights the fact that both the basic energy value and the size of the PV "premium" depend on energy market conditions; they may be larger or smaller in future years.

year, this is consistent with the number of PG&E feeders that actually reach capacity annually (PG&E, 2013a).

3.2.2. Applying model runs to PG&E feeders

We permuted each R1 result that was simulated with Berkeley weather data with data for each feeder in PG&E's "coastal" service territory, and each R3 result that was simulated with Sacramento weather data with each feeder in PG&E's "interior" territory. For each combination of taxonomy feeder and PG&E feeder that would require a capacity upgrade project within ten years, we computed savings as a ratio (ρ) between the net present savings and the original project cost:

$$\begin{aligned}\rho_{i,j}(X,\alpha) &= \frac{\mathrm{NPC}_{\text{original project}} - \mathrm{NPC}_{\text{deferred project}}}{\mathrm{NPC}_{\text{original project}}} \\ &= \frac{c_{\text{real}}(1+r)^{-y^0_{i,j}} - c_{\text{real}}(1+r)^{-y^d_{i,j}(X,\alpha)}}{c_{\text{real}}(1+r)^{-y^0_{i,j}}} \\ &= 1-(1+r)^{(y^0_{i,j}-y^d_{i,j}(X,\alpha))} \qquad (4)\end{aligned}$$

where NPC denotes net present cost, c_{real} denotes the real project cost, i indexes the PG&E feeder and j indexes the simulation results of each GridLAB-D taxonomy feeder (in the appropriate climate), r is the discount rate, and $y^0_{i,j}$ is the originally estimated year of the capacity upgrade project. $y^d_{i,j}(X,\alpha)$, the deferred year, depends on the year ten penetration level X and deployment scenario α.[5]

We then calculated $\rho_{\text{aggregate}}$, the total weighted average normalized savings in net present value across all GridLAB-D taxonomy feeders in the coastal and interior zones:

$$\rho_{\text{aggregate}} = \frac{\sum_{i\in R1, j\in R1} f_j\rho_{i,j} + \sum_{i\in R3, j\in R3} f_j\rho_{i,j}}{N}, \qquad (5)$$

where $N = 296$ is the number of feeders we estimate will require a capacity upgrade project in the next ten years, R denotes region ($R1$/coastal; $R3$/interior), f_j is the regional taxonomy feeder frequency from Table A.2, and N is the total number of feeders across all regions. Because $\rho_{i,j}$ values are ratios of present value to original value, Eq. (5) weights high- and low-cost projects equally. Therefore we have implicitly assumed that there is no correlation (negative or positive) between the cost of a project and its ratio ρ. We did not have access to the data required to test this assumption; to the extent project cost might be positively (negatively) correlated with ρ, our $\rho_{\text{aggregate}}$ measure will underestimate (overestimate) the distribution capacity deferral value of PV.

3.2.3. Scaling to PG&E's distribution capacity budget

We calculated the financial benefit of project deferral by multiplying $\rho_{\text{aggregate}}$ by the fraction of PG&E's distribution budget that could reasonably be affected by PV. We determined this fraction from PG&E records and forecasts of line and substation capacity upgrade expenditures in major work categories (MWC) 06 and 46, respectively (PG&E, 2012, Workpaper Table 12-5). Appendix C.2 explains which portions of these categories we included. Altogether, the categories deemed sensitive to PV impacts on peak loading constitute 93% of PG&E's 2012 distribution capacity budget ($133 million). For 2013–2016 we used nominal budget projections directly from PG&E (2012, Workpaper Table 12-5) and found that 83–89% of the budget in those years is projected to be sensitive to PV peak load reduction. The percentages are lower than in 2012 because the excluded work categories are projected to grow somewhat more quickly than the included categories. For 2017–2022 we used the average PV-sensitive budget for 2013–2016. The total net present cost of the expenditures deemed PV-sensitive is $1.2 billion (using $r = 5.1\%$).

By normalizing the model's results and applying them to the entire PV-sensitive distribution budget, the approach we use implicitly captures all measures – including those less expensive than full replacement of equipment, such as switching loads to different feeders – in the historical budget and forecasts. The analysis effectively assumes that the distribution of actions taken in response to PV penetration will not change, even if the *number* of capacity shortfalls does. Furthermore the analysis does not consider uncertainty in distribution capacity value forecasts, which are themselves a function of PG&E's own uncertainty on future distribution system maintenance activities and the limitations of working with a single year of PV and weather data (see discussion in Section 3.2.5).

3.2.4. Value of capacity deferral

Fig. 3 displays the net present value of distribution capacity project deferral, computed by multiplying $\rho_{\text{aggregate}}$ by the estimated peak-load-sensitive PG&E distribution budget. The total value of deferral increases at a decreasing rate, because low penetrations of PV push peak net load later in the day, when further PV provides less distribution capacity benefit. Though value increases with deployment rate, there is relatively little difference between immediate and intermediate rates. The total NPV of deferral is up to half of the estimated 10 year distribution capacity budget. Note also that if the large industrial "GC" feeders (discussed in Appendix A) accrue PV-related capacity benefits similarly to the weighted average of the feeders we modeled, the total value of deferral across all penetration levels and deployment trajectories would be about 19% higher.

3.2.4.1. Energy-levelized capacity benefit. To put the overall capacity project deferral benefit into perspective, we can levelize the capacity benefit across the kW h of PV generated throughout the ten year horizon. As with other levelized statistics we discount future energy production in addition to costs:

[5] Note that the real project cost, assumed to be independent of time, cancels from the ratio.

$$\text{Energy-levelized capacity benefit} = \frac{\text{net present value of deferral}}{\sum_{y=1}^{10} \frac{s_y E_{\text{PV,av}}(X_y)}{(1+r)^y}}, \tag{6}$$

where we compute energy production in year y as the *total* PG&E-wide PV production associated with each particular deployment and final penetration scenario.

Fig. 4 shows the result of this calculation. As with the total benefit, capacity project deferral benefit rises with PV penetration but with diminishing returns. Overall the range of levelized benefits is between 0.05 ¢/kW h and 0.21 ¢/kW h; this is roughly 0.3–1.5% of the average retail tariff in PG&E. These numbers are slightly less than previous estimates (e.g. 0.1–10 ¢/kW h in Darghouth et al. (2010)).

Recall, however, that we evaluated the present value of capacity deferral only on those feeders identified as having a capacity project in the first ten years of analysis. This subset of feeders is 10% of the number of feeders, and 20% of total MW capacity, in PG&E. Therefore if one assigned the capacity value only to those PV systems on feeders with deferred projects, the levelized value of those systems would be roughly five times greater (1/0.2) than the numbers reported in Fig. 4, or 0.25–1 ¢/kW h (roughly 1.8–7.5% of the average retail tariff).

Though earlier deployment always improves the NPV of the capacity benefit, the effect on the energy-levelized benefit is slightly different. As one might expect, levelized benefit is greatest with intermediate rates of deployment, where solar deployment (and energy production) roughly follows the feeder load growth trajectories.

3.2.4.2. Annualized capacity benefit. As an alternative, we normalized per kW of installed PV with the following metric:

$$CV_{\text{av}} = \underset{\text{(per unit of PV capacity)}}{\text{annualized capacity benefit}} = \frac{\frac{\text{net present value of deferral}}{\text{target PV penetration on all feeders}}}{\text{annuity factor}},$$

where we annualize in order to facilitate comparisons with annual distribution fixed charges as well as generation capacity costs at the conclusion of this section. To compute the annuity factor we used the same discount rate as before ($r = 5.1\%$). We also assumed benefits accrue over $n = 25$ years because, although we compute deferral benefits for feeders that require projects in the first ten years in the absence of PV, we count the cost of deferred projects for up to 25 years. With these assumptions the annuity factor is $\frac{1-(1+r)^{-n}}{r} = 13.95$ years.

Fig. 5 shows the result, with values ranging from nearly zero to more than \$6/kW-year. As one would expect, the value declines with increasing penetration and increases with the rate of deployment. As a point of comparison, at \$5.30/W (the 2012 average price for residential systems Barbose et al., 2013), the annualized *cost* of PV was on the order of \$380/kW-year in 2012. Moreover, if DOE's SunShot 2020 goal of \$1.50/W for residential solar is met (U.S. DOE, 2012), the annualized cost would be roughly \$110/kW-year. These numbers suggest that, for an average feeder, capacity value is unlikely to be a major contributor to PV investment decisions.

However, as mentioned in Section 3.2, we found that only 10 percent of feeders would require a project within ten years. Therefore dividing by PV capacity on *all* feeders dilutes the value of PV on feeders that *would* have projects. We computed the following metric to capture the capacity project deferral value on feeders with deferred projects:

$$CV_{\text{deferred}} = \text{deferred feeder annualized capacity benefit} = \frac{\frac{\text{present value of capacity deferral}}{\text{target PV penetration on } \textit{deferred} \text{ feeders}}}{\text{annuity factor}}. \tag{7}$$

We then estimated feeder-specific capacity project deferral value as follows, where i and j denote deferred PG&E feeders and GridLAB-D taxonomy feeders, respectively:

$$CV_i = CV_{\text{deferred}} \frac{\sum_{j \in R_i} f_j \rho_{i,j}}{\rho_{\text{aggregate}}} \tag{8}$$

where the normalized NPV of deferral, $\rho_{i,j}$, is defined in Eq. (4), f_j is the regional taxonomy feeder frequency from Table A.2, R_i is the subset of taxonomy feeders with the same regional designation (either interior or coastal) as PG&E feeder i, and $\rho_{\text{aggregate}}$ is defined in Eq. (5). This metric weights the average deferral value by the ratio of each feeder's normalized NPV of capacity deferral to the normalized average NPV of capacity deferral – in effect this gives the feeder-specific deferral value. Fig. 6 shows percentiles of capacity project deferral benefit on the subset of feeders with projects in the first ten years for the fast ramp scenario ($\alpha = -50$). Because we find that roughly 10% of PG&E feeders would require capacity projects within ten years, the percentiles in this figure are roughly ten times larger than they would be if computed across all feeders in PG&E. These numbers compare more

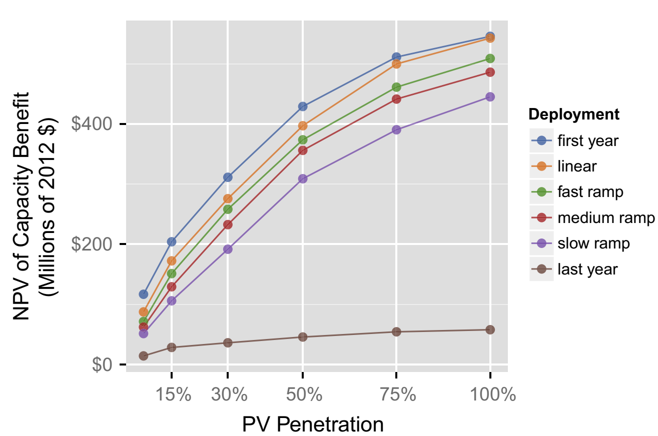

Fig. 3. PG&E system-wide capacity benefit.

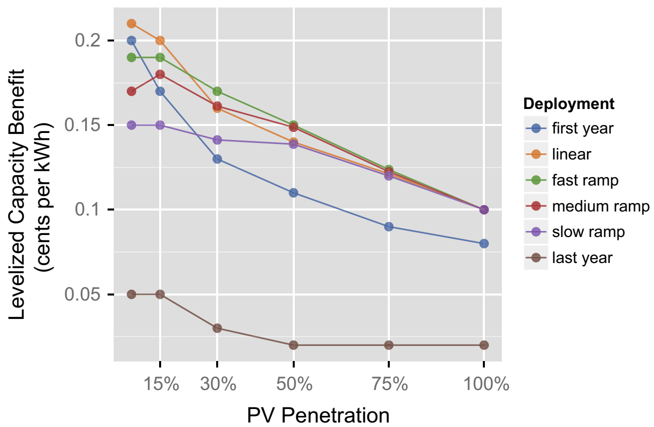

Fig. 4. Energy-levelized capacity benefit, computed with Eq. (6) and $r = 5.1\%$.

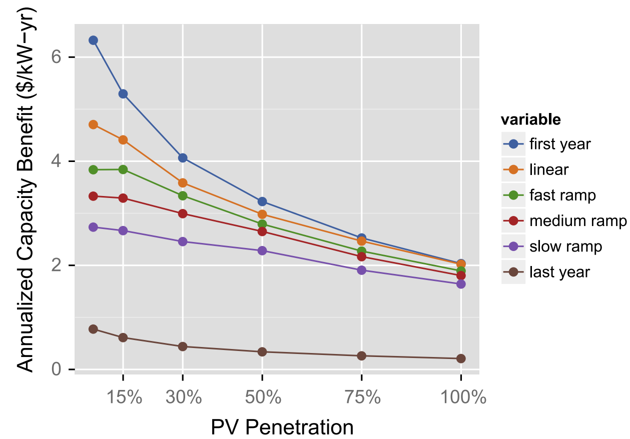

Fig. 5. Average annualized capacity benefit, computed using Eq. (7). Note that the benefit is normalized by total PV capacity, rather than PV capacity on only the deferred feeders.

favorably to current and projected annualized costs of PV, though on most feeders (and all in the percentiles we show) the benefits remain well below the cost of PV.

We can also compare these annualized numbers to the size of possible fixed charges on customer bills. Fixed charges (measured in dollars per month) allow utilities to collect revenue for their fixed costs without relying entirely on volumetric charges (measured in ¢/kW h), which sum to very small amounts for customers whose net energy consumption is very low due to installed photovoltaics. In 2013, California's AB327 authorized its Public Utility Commission to approve a charge of up to $120 per year, partially in recognition of the fact that owners of PV use less energy but still place burdens on infrastructure. However our results suggest that PV systems located where they help to defer distribution capacity projects could have *benefits* for infrastructure of the same order as the fixed charge. For example, at a low feeder PV penetration (7.5%) a 5 kW system would create $50 to over $300 per year benefit in terms of avoided distribution capacity upgrades; even at 100 percent penetration the benefit could be as high as $100 per year.

Though earlier studies suggested a large range of PV capacity values depending on model assumptions (e.g. Darghouth et al., 2010), in this case the input data themselves (circuit loading and peak load growth statistics) produce a large range of values, holding model assumptions constant. As we will discuss in the conclusions, this suggests that location-specific compensation for PV capacity benefits may be an effective strategy to minimize utility-wide distribution capacity upgrade costs. Implementing this type of tariff could be challenging from a regulatory and process perspective, though we note that Minnesota's recently approved "Value of Solar Tariff" methodology includes a location-specific capacity value, and it has received both positive (e.g. Draxten, 2013) and negative (e.g. Podratz, 2013) comments from utilities.

Appendix C.4 describes a discount rate sensitivity analysis; as one would expect higher discount rates result in lower deferral values; sensitivities in percent terms (e.g. the percent change in benefit due to increasing or decreasing WACC) are comparable for all WACC/ deployment trajectory combinations.

3.2.5. Caveats

Uncertainty in the output of distributed solar may prevent some capacity project deferral benefit from being realized during the investment planning process. For instance, utilities may conservatively overbuild distribution capacity to be prepared for an emergency that temporarily takes PV offline. Also capacity upgrade projects may be initiated sooner than absolutely necessary to economize on personnel and equipment in the area for other work. We view characterizing the magnitude of these effects as an opportunity for future research; for further discussion of these issues from a utility perspective see PG&E (2013b).

A related concern is that all results are based on one year of simulation, and cloudy or partly cloudy conditions could coincide with peak load conditions in another year. Based on historical solar radiation data and the timing of CAISO system wide peak demand, we estimate that the coefficient of variation of solar availability during peak demand is below 5% in both locations (see Appendix C.5 for detail). Though additional analysis is required in this area, we believe this variability is sufficiently low to suggest that our results apply outside of our year of analysis.

Finally, we were not able to validate the peak load shapes produced by GridLAB-D against actual feeder-level load shapes in the PG&E service territory. Our analysis in Part 1 compares GridLAB-D load shapes against load data from all of PG&E, all of CAISO, and an overall distribution of feeder peak loading times provided by PG&E under a non-disclosure agreement. Those results show that simulated peak times match well with PG&E and CAISO's actual late-afternoon peak times, but simulated loads drop off faster than PG&E and CAISO loads in the evening. This suggests that our simulations may

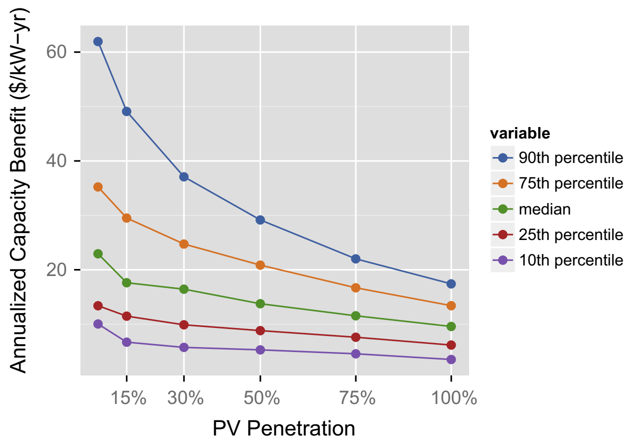

Fig. 6. Capacity benefit percentiles on deferred feeders. Because we find that roughly 10% of PG&E feeders would require capacity projects within ten years, the percentiles in this figure are roughly ten times larger than they would be if computed across all feeders in PG&E.

overestimate the *average* peak load reduction as PV pushes peak times later in the evening. On the other hand, the comparison with PG&E's peak time distribution shows that many individual feeders peak mid-day; on those feeders PV will be *more* effective at reducing peak load. On the whole there are likely to be many feeders where PV capacity value is significant. Identifying these feeders will require attention to existing distribution capacity and projected load growth as well as load patterns on high demand days.

3.3. Voltage regulators and voltage quality

As explained in Appendix B, PV can impact voltage regulator operation patterns. To the extent this increases or decreases regulator switching, maintenance requirements (and distribution company costs) could change. Using our physical results for voltage regulators (Appendix B and Part 1 of this series (Cohen and Callaway, 2016)) we can make general estimates of how regulator maintenance expenses might change.

Appendix C.3 describes the PG&E major work categories (MWC) related to voltage regulating equipment. We conclude that, from PG&E's 2012 budget, $1,382,000 could be affected by changes in tap-change activity. As we explained in Part 1 (Cohen and Callaway, 2016), GridLAB-D captures the effect of PV on changes in line regulator switching but not substation LTCs. If we assume that substation LTC switching changes in percentage terms in the same way as line regulators (this is a strong assumption because LTCs will respond more to transmission level variation in voltage), we can extrapolate our regulator results from Part 1 (Cohen and Callaway, 2016) to the system and estimate how much PV might affect overall regulator expenses. From Part 1, at the high end (100% penetration), PV increased regulator operations by 32%. Assuming line regulator and LTC maintenance requirements increase linearly with the number of tap changes, then maintenance expenses would also increase by 32%, or roughly $442,000 in 2012. In a more optimistic scenario where regulator operations decreased by 8% due to the presence of PV (in line with our "best case" simulation results) across the system, regulator maintenance expenses might decrease by $111,000. In reality both penetration scenarios might exist on different feeders in the system, in addition to intermediate and perhaps even more extreme cases. Therefore overall expense changes are likely somewhere between these bookend values. Note that the overall impact will be more favorable if the reduced current duty brought about by PV also extends regulator lifetime, but the sensitivity of regulator lifetime to reductions in current is heavily dependent on the regulator model and its pre-PV current duty, so we lack the data to estimate the magnitude of this effect. In any case, we conclude that any regulator maintenance cost changes – whether they are positive or negative – will be very small in comparison to the energy cost and capacity project deferral value of PV.

For comparison, PG&E's budget for addressing Voltage Complaint Projects Involving Secondary Distribution (MWC 06G) was forecast to be $2,800,000 in 2012; some fraction of MWC 06E (Circuits Reinforcement – Project Services Managed, forecast at $36,941,000 in 2012) is also dedicated to "primary distribution voltage correction work" (PG&E, 2012, pp. 12–20). As noted in Part 1, voltage quality on our simulated feeders was only mildly affected by PV, although we expect that in the field there will be some feeders where it will be a significant issue. Though our data are not sufficient to make a conclusive estimate of how frequently PV will actually trigger complaints or create serious enough problems to require additional work in the above mentioned MWCs, they suggest that these costs will also be relatively small.

3.4. Transformer aging and backflow/protection

As noted in Part 1, we observed minimal transformer aging across all of our simulated scenarios, with little change due to PV except with one particular feeder/climate combination (R3-12.47-3, Sac.). We do expect that PV will have some effect on transformer lifetimes in areas where they are loaded at or above capacity. In most cases, lifetime is likely to be extended as daytime transformer loading is reduced by generation on the secondary side. In some cases transformer lifetime may be decreased by large reverse power flows. Given uncertainty about existing transformer load shapes and ages it is difficult to estimate the size of the benefit (or cost) that PV could provide.

Similarly, we refrain from drawing conclusions about the effect of backflow caused by high PV penetrations (see Appendix B). The main concern regarding backflow is that it may require modifications to protection systems that were designed with only one-way power flow in mind. Determining whether such corrections are necessary on any given feeder requires a specialized protection analysis which is beyond the scope of this study.

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4. Conclusions

We found that PV provides a capacity deferral value of up to \$6/kW-year when averaged across the potential impact on all feeders in PG&E's service territory. However, when we disaggregate the results by feeder – some of which are much closer to requiring a capacity upgrade project and have load shapes that are better correlated with PV production – the capacity project deferral value can be as much as \$60/kW-year on a small subset of feeders. Though additional research is needed to understand how uncertainty in solar resource availability and future capacity upgrade expenses could impact these results, in general our modeling points toward significant capacity value heterogeneity across locations and feeders.

When viewed against a possible connection fixed charge (proposed to be on the order of \$120/year in California's AB327), the capacity deferral value of PV could be significant in some cases and inconsequential in others. Also when viewed against the cost to install PV (\$380/kW-year at the end of our study period (Barbose et al., 2013), but possibly as low as \$110/kW-year if the DOE's SunShot goal of \$1.50/W is met), the capacity deferral value of PV could be a significant incentive for some customers to install PV. There is some precedent for recognizing the capacity value of distributed PV (for example Minnesota's "value of solar" tariff or VOST, or capacity-based incentives for preferred locations (Neme and Grevatt, 2015)); our findings give strong evidence that location-specific credits are appropriate. In places without a such a program in place we suggest that this spatially heterogeneous value of PV could be embedded in retail fixed charges. This process could be streamlined with substation-level loading, load growth and capacity data. A full analysis of equity implications and administrative costs would be needed to determine the feasibility of locational credits.

Our physical feeder modeling indicates that voltage regulator operations could increase by 32% at the highest PV penetrations we studied. If voltage regulator maintenance scales linearly with the amount of operation, our results in this paper indicate that annual costs would increase by \$442,000 if all circuits in PG&E had 100% penetration – an extremely small amount of PG&E's roughly \$6 billion operations and maintenance budget in 2012, and much smaller than the roughly \$30–\$40 million annual capacity project deferral benefit we estimate that PV would provide at the same penetration. Though we do not have data to assess the heterogeneity of these impacts, our physical simulations suggest feeder location and design can significantly impact whether PV will create voltage problems, suggesting that proactive distribution planning may enable utilities to avoid these problems.

Overall our results suggest that average distribution-level economic impacts we measure are small and slightly positive. A large part of those positive impacts seem to be concentrated in a small number of circuits. Therefore to the extent these benefits *could* be reflected in incentives to customer-sited PV, we do not anticipate that they would support a significant expansion in total PV capacity in our study region. This suggests that significant PV penetration in distribution systems will be economically justified only when the *energy value* – ideally including environmental externalities such as CO_2 – reaches parity with the levelized cost of PV.

Acknowledgment

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Appendix A. Summary of inputs to physical simulations

A.1. Physical simulation inputs

Our study focuses on climate, photovoltaic production and infrastructure representative of PG&E's territory (Northern California). We chose this region in part for the prominence of distributed photovoltaics there and also because of California's ongoing policy debates on issues of net metering and retail tariff design. We also chose this region because we had access to feeder-level load growth rates. PG&E accounted for 38.3% of California's total energy consumption in 2012 (California Energy Commission, 2013). As explained in Part 1, we ran simulations over the 366 days between September 25, 2011 and September 24, 2012, inclusive. In this paper we focus only on results for Berkeley and Sacramento, because they are representative of PG&E's two major climate regions (coastal and interior, respectively). California peak demand during the selected year was fairly typical relative to the past decade, with a peak load of 46,846 MW in 2012 versus a high of 50,270 MW in 2006 (CAISO, 2013b).

We generated simulation results – as described in Part 1 of this two part paper – with GridLAB-D. GridLAB-D simulates distribution system operation over time, capturing load variation due to building occupancy patterns and ambient conditions. It models distribution system equipment including capacitors, voltage regulators, on-load tap changing transformers, and secondary distribution transformers. We used GridLAB-D version 2.3 with the forward–backward sweep power flow solver.

Table A.2
Assumed frequency of $R1$ and $R3$ feeders, adapted from Schneider et al. (2008).

Feeder	Assumed frequency, f_j (%)
R1-12.47-1	21
R1-12.47-2	23
R1-12.47-3	19
R1-12.47-4	17
R1-25.00-1	11
R1 gen. case – industrial[a]	9
R3-12.47-1	30
R3-12.47-2	30
R3-12.47-3	20
R3 gen. case – industrial[a]	20

[a] For our main analysis we conservatively assumed these feeders had no PV installed, because we lacked detailed load data needed to model them effectively.

As discussed in Section 2, we modeled the 8 PNNL distribution taxonomy feeders that correspond to the climate zones in our analysis. We chose not to model PV on General Industrial Case (GC) feeders (9–20% of feeders, according to PNNL) because they consist essentially of one industrial or commercial load and we did not have available an appropriately representative set of commercial and industrial load shapes. The feeder taxonomy also does not include networked urban cores, which represent 5–10% of the distribution system (Schneider et al., 2008). Frequencies for the remaining feeders, taken from Schneider et al. (2008), are listed in Table A.2.

We define PV "penetration" relative to a baseline (no PV) loading for each feeder as:

$$\text{PV penetration} = \frac{\sum(\text{PV system ratings})}{\text{Peak feeder load from baseline run}}$$

We populated houses at random with PV as necessary to vary penetration from zero to 100%. To isolate the effect of penetration from the effect of placement, we used the same random number seed in each scenario to ensure that houses with PV in lower penetration scenarios were a strict subset of those populated in higher penetration scenarios. We used the same random ordering of houses for PV placement in each test location, and modeled PV as a unity power factor "negative load".

Appendix B. Summary of simulation engineering results

B.1. System losses

By serving loads locally, system losses decrease with PV penetration. As with prior studies (Quezada et al., 2006; Widén et al., 2010; Navarro et al., 2013; Thomson and Infield, 2007) we found that on some feeders losses begin to increase at very high penetrations due to heavy reverse flow conditions. On most feeders, losses continued to decrease to the maximum penetration level we studied (100%), and feeder type had a stronger influence on the total magnitude of losses than did climate.

B.2. Peak loading

At 100% penetration, PV reduced peak load by 6–35%. Load reductions are well below the penetration level because peak demand occurs later in the day than peak PV production. In general we found that location (which drove load and PV production profiles) had a stronger influence on peak load reduction than feeder type.

B.3. Transformer aging

Transformer aging is driven by thermal degradation; higher loading results in greater losses and accelerated insulation aging. In general, we observed minimal aging in all scenarios and penetration levels, with a mean equivalent aging of up to 0.29 year in one scenario (R3-12.47-3, Sac.) and all other scenarios having mean aging less than 0.001 year. We sized transformers at or just above their baseline peak load (Cohen and Callaway, 2013); aging would have been faster if the transformers were undersized.

B.4. Voltage regulators

Voltage magnitude on a conductor typically declines in the direction of power flow, and as power flow increases, voltage declines further. There are three basic types of equipment that maintain voltage within prescribed bounds in a distribution circuit: on-load tap changers (LTC) located at distribution substations, capacitor banks and voltage regulators. LTCs and voltage regulators automatically adjust voltage by changing the "turns ratio" on an in-line transformer to maintain voltage within a prescribed range. We only studied voltage regulator impacts. We neglected LTC impacts because their operation is a strong function of transmission level voltage and because GridLAB-D does not model transmission impedance (meaning LTC output voltage is minimally affected by PV variability); we neglected capacitor bank switching because, to the extent it occurs, is often scheduled (rather than based on a voltage measurement). See Cohen and Callaway (2013) for more discussion. Overall we found that the change in the number of tap changes on the regulators ranged from negative 10% to positive 30%.

B.5. Voltage quality

In general, across all penetrations and feeders, we found voltages to be relatively well-controlled, with most runs having less than 0.002% of readings out of the ANSI standard range (virtually unchanged from the base case), and the worst case (R3-12.47-3, Sac.) having 0.32% of readings out of range at 100% penetration. This is consistent with prior work suggesting that many feeders can support high penetrations of PV without voltage violations (Hoke et al., 2013). Across the scenarios we investigated, the propensity for voltage excursions to occur was most strongly driven by location.

B.6. Reverse power flow

We studied the incidence of negative real power flow ("backflow") through the substation, which can be a proxy for protection equipment problems and higher interconnection costs. At 50% penetration, 8 of the 16 scenarios exhibited occasional backflow, but no more than 1% of the time in any one scenario. At 100% penetration, all scenarios experienced backflow at least 4% of the time.

Appendix C. *C.1. Comparing simulation and PG&E end-use consumption*

For each feeder, we calculated end-use consumption by subtracting system losses from substation energy at 0% PV penetration and we then computed a weighted average end-use consumption for the sample using the same weighted average approach as in Eq. (2).

We factored in future load growth by scaling consumption to the 2012–2022 projections for PG&E published by the California Energy Comission (CEC) (California Energy Commission, 2012, p. 6; California Energy Commission, 2013, pp. 36–40). These projections include net load reductions due to customer sited PV, since the CEC assumes that a higher percentage of generation will come from this source over time. The CEC provides high and low estimates of customer PV generation, with a mid-range of 1% of PG&E's consumption in 2012 and 2% in 2022 (California Energy Commission, 2012, p. 6, 28). To convert the CEC consumption figures to end-use consumption, we multiplied the CEC's "CED 2011 Revised-Mid" forecasts by one plus the solar generation ratio, scaled linearly from 1–2% over the 10 year period.

The ratio of PG&E consumption to that in our sample, denoted s_y with y indexing years, ranged from $s_1 = 5720$ to $s_{10} = 6453$.

C.2. Portions of PG&E capacity upgrade budget affected by PV

In consultation with PG&E (PG&E, 2013a), we assumed the following subcategories are influenced by PV's contribution to peak loading: MWC 06A (Feeder Projects Associated with Substation Work), MWC 06D (Circuits Reinforcements (DE Managed)), MWC 06E (Circuits Reinforcements (PS Managed)) and MWC 46A (all projects). We excluded some smaller expenses that would not likely be influenced by PV's peak load reduction: 06B (Overloaded Transformers), 06E (Reinforce Circuit > 6000 customers per feeder), 06E (Complete Mainline Loops per Standard), 06G (Voltage Complaints (Includes PEV)), and Line Voltage Regulator Revolving Stock.

C.3. Portions of PG&E voltage maintenance budget affected by PV

There are several PG&E major work categories (MWC) related to voltage regulators. MWC BK (Distribution Line Equipment Overhauls) is a category that includes needed overhauls for line reclosers and regulators; in 2012 expenses of $2,645,000 were forecast for this purpose (PG&E, 2012, pp. 5–34). Regulators constitute about 41% of the total units of line equipment (regulators + reclosers) PG&E (2013a). Under the coarse assumption that the unit cost to overhaul a regulator is the same as the unit cost for a recloser, regulator overhaul expenses are roughly $1,085,000. MWC 48 (Replace Substation Equipment) includes several "Subprograms < $1M", including a line item for regulator replacements projected to be $297,000 in 2012 (PG&E, 2012, Workpaper Table 12-5). Some LTC replacement work also takes place under MWC 54 (Distribution Transformer Replacements) which had an overall forecasted value of $61,005,000 in 2012 (PG&E, 2012, pp. 13–14). However, most of this expense is for general substation transformers not LTCs, and projects are usually triggered by factors unrelated to the LTC such as dissolved gas analysis of the transformer oil; in these cases the LTC is replaced in the course of a larger project rather than due to wear on the LTC itself (PG&E, 2013a). Therefore we conclude that MWC 54 expenses are unlikely to be affected by changes in LTC operation triggered by PV. This leaves us with a total projected 2012 regulator budget of $1,382,000 from MWC BK and 48 that could be affected by changes in tap-change activity.

C.4. Discount sensitivity analysis

Because capacity value benefits depend on events that occur in the future, the magnitude of the benefit depends on the assumed WACC (or discount rate). Therefore we ran the model for different values of α (PV deployment rates) and using a WACC of 5.0% and 10.0% (less and greater than the originally assumed WACC of 7.6%). Fig. 7 shows the result. As expected, higher discount rates make deferral more desirable. Though immediate deployment (fast ramp) has the highest sensitivity in absolute terms, sensitivities in percent terms (e.g. the percent change in benefit due to increasing or decreasing WACC) are comparable for all WACC/deployment ramp combinations.

C.5. Annual peak solar variability

To quantify solar variability in peak demand conditions we collected annual peak demand times for CAISO and computed solar availability in each year's peak demand hour from data from the National Renewable Energy Laboratory's National Solar Radiation Database (NSRDB). The closest NSRDB stations to our analysis regions are Oakland International Airport and Sacramento Metropolitan Airport. For each year that CAISO reported peak

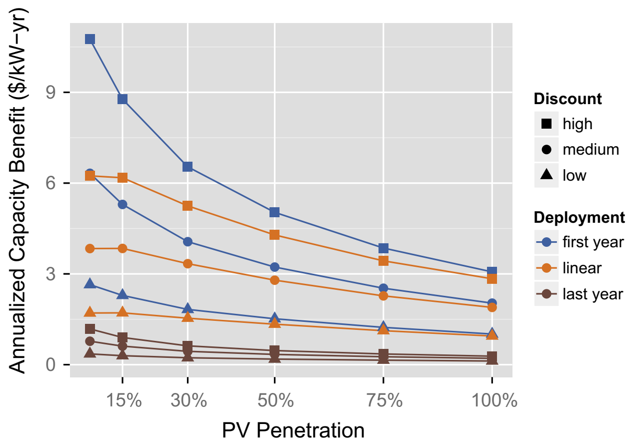

Fig. 7. Sensitivity of capacity benefit to discount rate.

demand and NREL reported solar radiation (1998–2009), we computed the ratio of global horizontal radiation to extra-terrestrial horizontal radiation. We then computed the coefficient of variation (CV) of that ratio (i.e. the standard deviation divided by the mean) for each location, with the results being $CV_{Oakland} = 4.4\%$ and $CV_{Sacramento} = 4.8\%$.

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Effects of distributed PV generation on California's distribution system, Part 1: Engineering simulations

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Abstract

Deployment of high-penetration photovoltaic (PV) power is expected to have a range of effects – both positive and negative – on the distribution grid. The magnitude of these effects may vary greatly depending upon feeder topology, climate, PV penetration level, and other factors. In this paper we present a simulation study of eight representative distribution feeders in three California climates at PV penetration levels up to 100%, supported by a unique database of distributed PV generation data that enables us to capture the impact of PV variability on feeder voltage and voltage regulating equipment. We find that feeder location (i.e. climate) has a stronger impact than feeder type on the incidence of reverse power flow, reductions in peak loading and the presence of voltage excursions. On the other hand, we find that feeder characteristics have a stronger impact than location on the magnitude of loss reduction and changes in voltage regulator operations. We find that secondary distribution transformer aging is negligibly affected in almost all scenarios.

Keywords: Distribution system; Distributed photovoltaics

1. Introduction

As the deployment of distributed photovoltaics (PV) accelerates, researchers and power industry professionals have increasingly attended to the impacts – both positive and negative – that PV might have on the distribution system. As discussed in Katiraei and Aguero (2011), areas of concern include PV's effect on:

- System losses.
- Peak load (which impacts capacity investments).
- Transformer aging.
- Voltage regulator mechanical wear.
- Power quality, particularly voltage magnitude.
- Reverse power flow and its effect on protection systems.

Prior work in this area consists largely of case studies that use simulations to examine a selection of these issues in detail for a single feeder or a single climate, e.g. (Quezada et al., 2006; Shugar, 1990; Woyte et al., 2006; Thomson and Infield, 2007; Navarro et al., 2013; Widén et al., 2010; Aukai et al., 2012; Bucher et al., 2013a). Results in these papers range from finding that distributed PV can cause resistive losses to *increase* at relatively low penetrations to finding that resistive losses continue to decline up to very high penetrations. Of those papers that examine the impact of PV on voltage excursions, results range from very positive (i.e. acceptable voltages at all penetration levels (Widén et al., 2010)) to negative (i.e.

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unacceptable voltages at high penetration levels (Navarro et al., 2013)).

However, because distribution systems are highly heterogeneous in terms of topology, climate and loads served, it can be difficult to draw generalizations from these case studies. Our objective is to fill this gap by studying distribution feeder operation for ranges of climates, PV penetrations and feeder topologies that have not been investigated before. We are aware of three existing studies that examine a diversity of climates and feeder architectures. In two (Paatero and Lund, 2007; Hoke et al., 2013) the simulations are driven with hourly solar irradiance data from a single location for each feeder. Therefore these studies cannot provide insight into how cloud transients and geographic diversity of distributed PV systems will influence distribution system operation. A third study (Nguyen et al., 2015, 2016) is notable in that it simulates the operation of five different feeders with spatially heterogeneous PV at fast time scales. In that study the PV production data were synthesized with an innovative approach to produce high resolution PV data from sky imagers. However, PV production data are synthesized with imager data from a single location, the locations of the feeders are not revealed, and a single representative normalized daily load profile was used for all loads and in all simulations. Though Nguyen et al. do enable new investigations into the effect of spatial diversity on feeder operation, without a full year of simulation with geographically varying loads and PV production, one cannot assemble a complete picture of PV's impacts on distribution system operations.

This is the first paper in a two-part series that quantifies the physical impacts of spatially heterogeneous PV over a year of distribution system operation in different climates and on different feeders (Part 1, this paper) and applies those physical results to an economic framework that quantifies distributed PV's impact on distribution system operation and maintenance costs (Part 2, Cohen et al., 2016). The specific aim of this paper is to evaluate some of distributed PV's impacts across a diversity of conditions and to inform policy makers and utility decision-makers regarding how extensive these impacts might be at penetrations that are rare today but could be prevalent in the future.

The key points of distinction from earlier studies are that we (1) run simulations with real, spatially distributed short time scale production PV data set and (2) examine a larger number of impacts, climates and feeder types. In addition to studying voltage excursions, resistive losses, incidence of reverse flow and impact on peak loading – as have the aforementioned papers, to varying degrees – we report on loss of life in secondary transformers and changes in operation in voltage regulators. Nguyen et al. (2015) is the only other paper we know of that addresses the issue of voltage regulation in detail, though only for three days of simulation. The PV data set comprises highly distributed production from residential and small commercial PV systems recorded over a full year at time intervals as small as one minute. By looking at all these factors together across different climates, feeder types and PV penetrations, we gain insight into what drives both negative and positive effects of distributed PV in distribution systems. This article is based on a prior conference paper (Cohen and Callaway, 2013), and expands it by covering more climates, adding a detailed comparison of simulated load shapes to actual load shapes, and presenting new observations about the importance of geographic diversity.

Our central findings are as follows: As one might expect, feeder type – rather than location – has the strongest influence on the total reduction in resistive losses. Conversely, peak load reduction, voltage issues and incidence of reverse power flow caused by PV depend more on location (climate) than on feeder type. As we will describe, impacts on voltage regulators are small and can either increase or decrease relative to a baseline without PV, depending on feeder type (and independent of location).

Though we investigate a very large range of impacts in this paper, there are other impacts that are outside of our scope. For example, we did not investigate the impact of the harmonic content of PV inverters on power quality and transformer aging. We also limit our investigation of protection equipment impact to assessing the prevalence of reverse flow conditions. Furthermore, though our simulations captured the effect of phase imbalances that might occur from random placement of single phase PV on a three phase network, we did not investigate scenarios where we deliberately loaded one phase with more or less PV than others. These omissions and others are due to space, data and modeling limitations, and they merit further systematic investigation in future research.

2. Methods

In this section we summarize our simulation methods and data; please see Appendix A for additional detail.

We used GridLAB-D to model distribution circuits due to its integration of power flow analysis and time-varying load models, availability of representative feeder models, and open-source license. GridLAB-D simulates house-level electrical demand based on time of day and climate data (see Appendix A.4). The developer of GridLAB-D, Pacific Northwest National Lab (PNNL), compiled a set of representative "taxonomy" feeders drawn from utilities throughout the United States (Schneider et al., 2008). PNNL assembled the taxonomy set by first collecting 575 feeder models from a range of investor- and municipally-owned utilities and rural cooperatives in the United States. PNNL then identified a set of 23 taxonomy models from the set of 575 via a systematic clustering analysis. In this paper we focus on taxonomy feeders associated with California climate zones: five feeders in region 1 (R1, temperate west coast) and three in region 3 (R3, desert southwest), see Table 1. Each of these feeders comprises predominantly overhead lines. Though the original PNNL sample was

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Table 1
Summary of simulated feeder characteristics and figure legend.

Name[b]	Serves[a]	Nominal peak load (MW)[a]	Dist transformers	Residential load[c] (%)	Approx length (km)	Baseline peak load (MW)			PV profiles selected for use		
						Berk.	L.A.	Sac.	Berk.	L.A.	Sac.
R1–12.47–1	Moderate suburban & rural	7.15	618	93	5.5	5.56	5.38	7.59	21	38	26
R1–12.47–2	Moderate suburban & lt. rural	2.83	264	84	10.3	2.00	2.04	2.82	30	30	30
R1–12.47–3	Moderate urban	1.35	22	13	1.9	1.27	1.25	1.60	10	10	8
R1–12.47–4	Heavy suburban	5.30	50	57	2.3	4.31	4.09	5.65	12	17	12
R1–25.00–1	Light rural	2.10	115	2	52.5	2.35	2.23	3.00	28	23	30
R3–12.47–1	Heavy urban	8.40	472	32	4.0	6.64	6.30	8.70	20	31	25
R3–12.47–2	Moderate urban	4.30	62	0	5.7	3.45	3.27	4.40	13	22	18
R3–12.47–3	Heavy suburban	7.80	1,733	84	10.4	7.54	7.00	9.67	56	48	55

In figures, shape indicates Berkeley (■), Los Angeles (•) and Sacramento (▲) results. Black symbols with dashed lines show means for each location.
[a] Schneider et al. (2008).
[b] Climate region of origin is indicated by R1 (temperate west coast) or R3 (arid southwest). Nominal voltage is designated by 12.47 or 25.00 (kV).
[c] Approximate percentage of peak load that is residential, calculated from planning loads on the PNNL taxonomy feeders.

neither random nor exhaustive, these feeders allow us to explore a broad range of PV's potential impacts.

We simulated each of the eight feeders in three California locations – Berkeley, Los Angeles and Sacramento – during the 366 days between September 25, 2011 and September 24, 2012, inclusive. We chose these locations and time span due to the availability of high-resolution PV generation and weather data. California peak demand during the selected year was fairly typical relative to the past decade, with a peak load of 46,846 MW in 2012 (CAISO, 2013b).

The PV integrator SolarCity provided us with a database of instantaneous power at about 7000 PV systems in California under the terms of a non-disclosure agreement. All the inverters are single phase and provide data on the quarter hour; for this project SolarCity also sampled a number of inverters at the fastest available time step of one minute.

We obtained one-minute temperature, humidity, and solar irradiance for Berkeley from Lawrence Berkeley National Laboratory (Fernandes, 2012) and for Los Angeles and Sacramento from SOLRMAP at Loyola Marymount University and Sacramento Municipal Utility District (NREL, 2012). The temperature, humidity and irradiance data determined HVAC load in GridLAB-D but were not used to simulate PV generation, which was instead extracted from the SolarCity database. By using generation data sources located not far from the weather stations we preserved correlation between air conditioning load and PV generation.

We used electrical connectivity and conductor lengths in combination with the graph layout utility Graphviz to create a geographic layout for each feeder. We then used ArcGIS to superimpose the resulting feeder layouts on the SolarCity profile sources and ran a "nearest neighbor" query to assign each distribution transformer to the closest SolarCity profile with acceptable data quality.

To test various levels of penetration, for each GridLAB-D run we populated only a portion of the houses with PV, defining penetration as:

$$\text{PV penetration} = \frac{\sum (\text{PV system ratings})}{\text{Peak feeder load from baseline run}}$$

We tested PV penetration levels of 0%, 7.5% 15%, 30%, 50%, 75% and 100%. We chose this range because 15% penetration is a "rule of thumb" for penetration levels beyond which negative PV impacts may emerge (Coddington et al., 2012), and we sought to explore penetration levels well beyond that level. 100% penetration corresponds to between 50% and 65% penetration by energy, as depicted in Appendix Fig. A.7.

We placed PV randomly across the available house models and used the same random number seed for all scenarios to ensure that PV was placed at houses in the same order for each climate (Berkeley, Sacramento, Los Angeles), and that all systems populated in lower penetration runs were also populated in higher penetration runs. We modeled the PV as a unity power factor "negative load".

Appendix A contains additional details on adjustments to PV and transformer sizing that were necessary to run the model.

3. Results

3.1. System losses

We recorded instantaneous system losses (including transformer and line losses) every fifteen minutes. As shown in Fig. 1a, we found that increasing PV penetration decreased system losses, with diminishing effects at high penetrations. The impact of PV on losses was similar across the three locations, but varied considerably by topology, with losses reduced by anywhere from 7% (R3-12.47-3) to 28% (R1-25.00-1) at 100% penetration. In particular, feeders with higher nominal peak loads (see Table 1) tended to have less loss reduction with increasing PV, though this trend was not universal. We also found, unsurprisingly, that the feeder that experienced the largest reduction in

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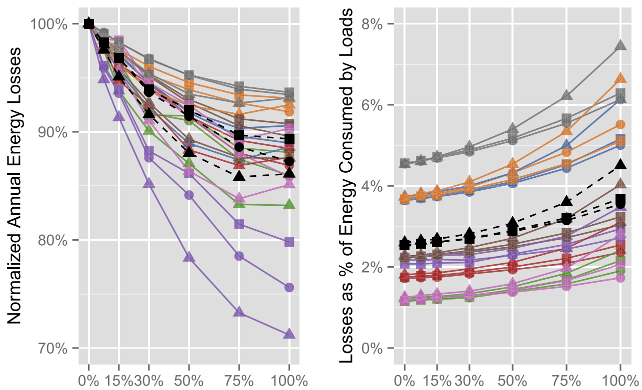


(a) Normalized system losses.

(b) Losses as a percentage of load energy supplied by the grid.

Fig. 1. Left: Normalized system losses. See Table 1 for key.

with peak PV production. In California, however, load typically peaks later in the day than PV production, and therefore peak loads are reduced by only a fraction of the PV's rating.

As shown in Fig. 2, we observed that PV generally reduced peak loads by much less than the penetration percentage. In contrast to system losses, location (i.e. climate) had a strong effect on the peak load reduction impact of PV, with Sacramento and Berkeley showing more significant reductions than Los Angeles. Fig. 2a shows the normalized peak load as a function of PV penetration, whereas Fig. 2b shows the peak reduction as a percentage of the solar penetration. Fig. 2b illustrates that low penetrations of PV can be quite effective at reducing peak loads, although this is not true in all cases. Peak load reduction effectiveness diminishes as penetration increases because early increments of PV tend to reduce daytime peaks, causing the new peak to be in the evening when PV contributes less power.

Fig. 3 illustrates trends in the timing of peaks as PV penetration increases. Without PV, peak loads arrived in August 2012 for most Sacramento feeders and half of the Los Angeles feeders, while Berkeley feeders generally peaked in fall 2011 or June 2012. Peak times were widely dispersed between 14:22 and 17:18. However, a 7.5% penetration of PV was sufficient to eliminate August peaks for all but one Los Angeles feeder, shifting their peaks to the later afternoon during a relatively warm spell in October 2011. Berkeley peaks, while initially shifting towards the summer, were ultimately also moved to the fall by high penetrations of PV. Meanwhile the Sacramento peaks, driven by larger air conditioning loads, remained in the summer at all levels of penetration, although moving noticeably later in the afternoon. In all locations, peaks were moved later in the day as PV reduced daytime usage.

We note that these simulations cover one particular year that was chosen primarily for PV data availability. It may not include extreme weather or other events that would drive true system peaks in the long term. Also, because

percent losses was also the longest. On average, reductions in Sacramento are greater than LA or Berkeley, and we attribute this result to the fact that Sacramento has higher energy penetrations for a given capacity penetration (Fig. A.7).

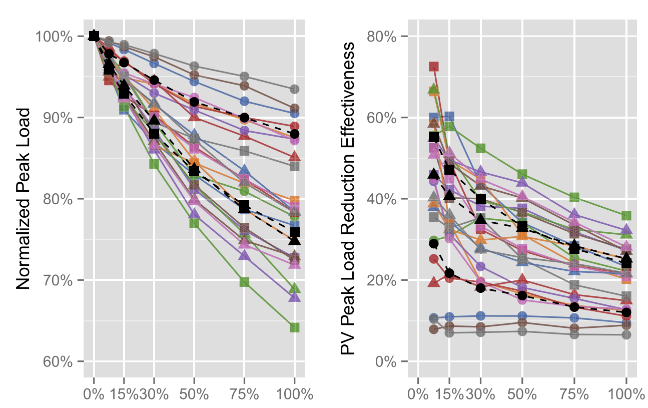
We attribute the reduced marginal effect of PV at high penetrations to the fact that losses are proportional to current squared; the more PV reduces power (and thus current) flow on the lines, the less effect further reductions will have on losses. For some feeders (mainly in Sacramento) losses *increased* as penetration rose from 75% to 100%, presumably because the losses associated with high "backflow" currents at certain times began to exceed the losses "saved" at other times when net current flow was lower.

Other studies have found that resistive losses increase with penetration (Quezada et al., 2006; Widén et al., 2010; Navarro et al., 2013; Thomson and Infield, 2007). However, consistent with Nguyen et al. (2015), our finding is that on *most* feeders we study, losses continue to decline up to 100% penetration. We note that in the feeder/location pairs here, location seems to determine whether or not losses begin to increase in the range of penetrations we examined, but that the total magnitude of losses is much more strongly influenced by the feeder type.

Fig. 1b shows that losses as a percentage of energy consumed by loads from the grid (i.e. as a percentage of utility wholesale power purchases) generally increase with PV penetration. This is likely because most of the load reduction happens off-peak, when system losses are lower than on-peak.

3.2. Peak loading

We computed peak load as the maximum fifteen-minute rolling average of one-minute measurements at the substation. The extent to which PV reduces feeder peak load depends largely on the timing of the peaks. Clearly, peak load reduction will be greatest if peak load is coincident



(a) Normalized peak loads.

(b) Ratio of peak load reduction to penetration

Fig. 2. Effect of PV on peak loads. See Table 1 for key.

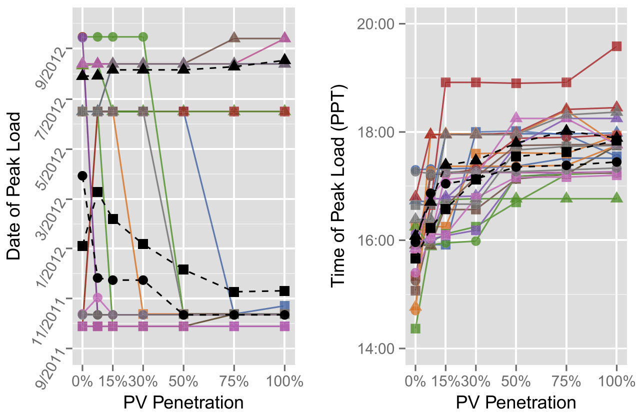


Fig. 3. Date and time of peak loads. The time reported is the first minute of the peak fifteen-minute period. See Table 1 for key.

GridLAB-D produces the load shapes internally, it is important to consider how well the simulated feeder load shapes align with feeder load shapes actually found in California. We do not have access to a large enough corpus of load shapes to do a rigorous analysis of this issue, but a high-level comparison will suffice to contextualize our findings. Fig. 4 shows the average hourly load and PV generation for each of the simulated feeders on August 13, 2012, which was the day CAISO recorded its peak demand for 2012 (CAISO, 2013b). It is also the peak demand day for five simulated Sacramento feeders, though not for any Los Angeles or Berkeley feeders. Each individual profile is normalized against the peak hour for that profile. As in the other figures, the locational means are straight averages of the eight normalized feeder simulations, i.e. the feeders are not weighted by their size or expected frequency of occurrence in the field. The load plot also shows normalized CAISO system load (larger green circles) and PG&E system load (larger blue circles).

From this figure we can see that the simulated peaks match well with the PG&E and CAISO peaks in the 15:00–16:00 range. However, the simulated feeders universally drop in demand more quickly than the CAISO system. Note from the bottom panel in Fig. 4 that PV production goes to zero after the simulated load drops, but before any significant drop in CAISO load. This suggests the possibility that peak demand might be relatively unaffected by PV in the CAISO system, but strongly affected in our simulations.

This simple one-day comparison ignores several factors that are important when calculating annual peak demand reduction, such as load variation within each hour and the fact that PV often shifts the peak to a different day, rather than a different time on the same day. Also, the comparison to an overall system load profile greatly obscures the wide variation of individual feeder profiles that comprise it. For instance, SCADA data provided by PG&E under the terms of a nondisclosure agreement indicates that on August 13, 2012 the most common hours for feeders to peak were 16:00 and 17:00, but each of these hours only accounted for about 16% of feeders, with 37% peaking earlier (including 10% before noon) and 31% later in the evening (Carruthers, 2013). Thus, it is likely that the simulated load shapes are a good match to some subset of California feeders and therefore the reported peak load reduction is achievable in some locations. However, the fact that the simulated feeder profiles are not a good match for the general system profile in the evening indicates that it would be optimistic to expect the simulated peak load reduction to occur universally across California.

3.3. Transformer aging

GridLAB-D 2.3 implements the IEEE Standard C57.91 Annex G (IEEE, 1996) method for estimating transformer insulation aging under various loading conditions. GridLAB-D implements the method for single phase center tapped transformers only. This is the most common type of transformer on the taxonomy feeders, but one feeder (R3-12.47-2) did not have any so it was excluded from the aging analysis. In the Annex G model, a “normal” year of aging corresponds to the amount of insulation degradation expected if the transformer hot spot were at a constant 110 °C throughout the year. A transformer that is often

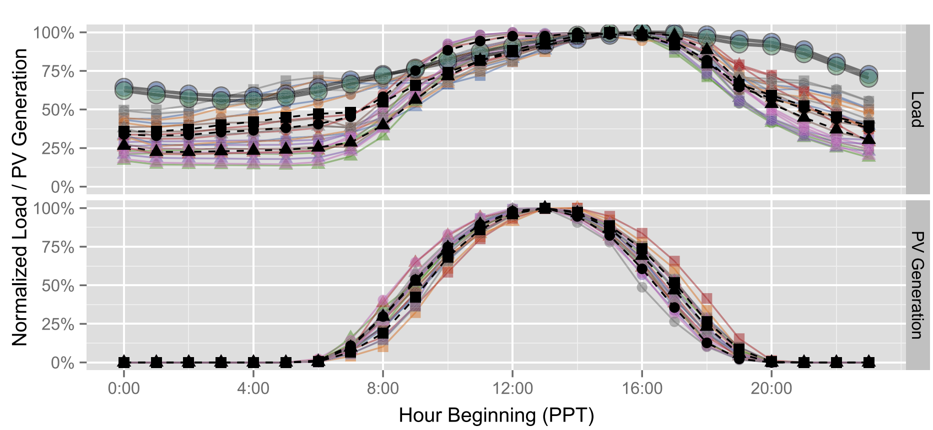


Fig. 4. Normalized hourly load and PV generation profiles for August 13, 2012. Normalized PG&E system load is shown by larger blue circles and CAISO load by larger green circles (CAISO, 2013a).

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overloaded will age more than 1 y in a year, and thus may need to be taken out of service due to insulation degradation before its rated lifetime. On the other hand, one that is loaded below its rating will age less than 1 y per year, and will be unlikely to have its insulation fail prematurely.

In general, we observed minimal aging in all scenarios and penetration levels, with a mean equivalent aging of up to 0.29 y in one scenario (R3-12.47-3, Sac.) and all other scenarios having mean aging less than 0.001 y. We attribute this slow aging to the fact that the transformers were conservatively sized at or above their baseline peak load (see Section Appendix A.10). However, in R3-12.47-3 (Sac.) at PV penetrations of 30% and above we did observe a small number of transformers aging quite rapidly, up to 166 y during the simulated year (all other scenarios had maximum individual transformer aging less than 0.38 y per year). These few rapidly aging transformers are likely at a location where net PV generation is often higher than the load they were sized to handle, and in reality they would need to be upgraded to handle this backflow.

3.4. Voltage regulators

Tap-changing voltage regulator wear and tear is driven primarily by the number of tap changes the device must perform and the current that it handles during operation. In our simulations, tap changes at the substation LTC were on the order of 20 per day. However the count was not affected by topology, climate or PV penetration, varying between 7166 and 7243 changes across all model runs over the year of simulation – a difference of only 1%. This small difference is because the models did not include a transmission impedance component, with the transmission voltage instead following a fixed schedule of values recorded from an actual substation in the U.S. Western Interconnection (WECC). The substation LTC operates to maintain voltage immediately downstream within the deadband despite fluctuations in the WECC schedule, and is insensitive to downstream changes in load. Due to the lack of a transmission model, our simulations do not provide reliable insight on LTC response to PV.

The two mid-feeder regulators in the simulation (at R1-25.00-1 and R3-12.47-3) do have simulated impedances and varying loads both upstream and downstream and thus exhibit more variation. Fig. 5a shows that PV has little effect at R3-12.47-3 until 50% penetration, at which point tap changes begin rising noticeably. This result echoes other work (Mather, 2012; Aukai et al., 2012) and concerns that PV variability will increase regulator maintenance needs, particularly in studies with multi-megawatt plants embedded in distribution systems (Lave et al., 2015). However, the present study – which focuses on many distributed rooftop systems rather than a small number of large systems – shows a relatively small total change in the number of control actions. We believe this is due to the fact that fast time scale variability in PV output is a relatively small amount of the total variability in PV output (Lave et al., 2013), particularly in heavily distributed scenarios such as ours. Consequently the number of control actions is largely driven by the diurnal range of net load. At low to moderate penetrations, the range of net demand has the tendency to *decrease* as PV reduces peak demand but does not push mid-day demand below the night time minimum. However at higher penetrations, the range of net demand grows as peak net demand is relatively unaffected (see Fig. 2) but mid-day net demand begins to drop below the night time minimum. These results indicate that in some cases PV could in fact *reduce* voltage regulator maintenance needs at intermediate penetrations.

We examined two sensitivity scenarios to study the impact that the PV data had on the regulator results. To produce the dotted lines in Fig. 5 we used the single PV profile with the most one-minute data available (82% of days) at all PV sites. The dashed line shows the same scenario with the one-minute data downsampled to fifteen-minute resolution; this intermediate scenario helps us to distinguish the effect of the one-minute data from the effect of eliminating geographic diversity. We limited the sensitivities to Los Angeles because this was our source of one-minute data. Fig. 5a suggests that geographic diversity reduces tap change frequency (because the solid lines which include geographic diversity fall well below their corresponding single-profile dotted and dashed lines) and that fifteen-minute PV data is a reasonable proxy for one-minute data when studying regulator behavior (because the dashed lines track their corresponding dotted lines closely). Note, however, that for geographically concentrated PV or lower voltage distribution systems, faster time scale data may still be required (Bucher et al., 2013b).

It is possible that with PV data on even finer time scales (faster than once per minute) a different pattern of regulator activity would emerge. However, we hypothesize that this is not the case for several reasons. First, as we discussed in the previous paragraph, the total amount of regulator action appears to be driven by diurnal variability (a daily occurrence) rather than partly cloudy conditions. Second, since regulators generally have a response lag on the order of 30 s, very brief fluctuations in PV are likely to result in voltage changes on the feeder rather than increased regulator activity.

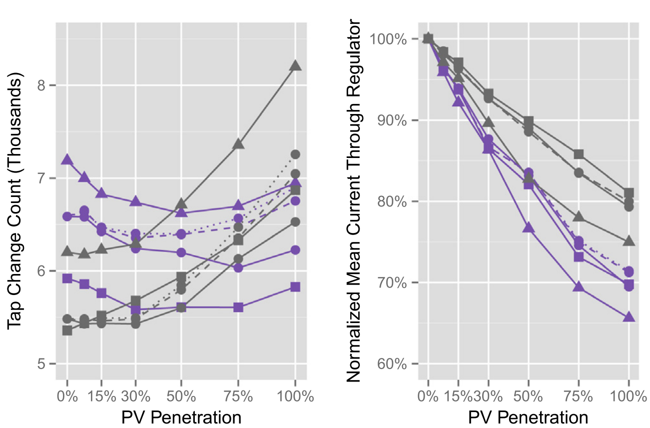
The effect of PV on regulator current duty was more consistent than the effect on tap changes, as illustrated by Fig. 5b. With PV reducing the downstream load, current through the regulator declines steadily as penetration increases. This suggests that even in cases where PV increases a regulator's activity, its expected lifetime may stay the same or even increase because each tap change is less destructive under lighter current duty. Our sensitivity runs suggest that neither geographic diversity nor the use of one-minute resolution data has a substantial effect on regulator current duty. We note that changes in current duty are more pronounced in Sacramento, an effect attributable to Sacramento's higher energy penetrations for a given capacity penetration.

3.5. Voltage quality

We recorded voltage at all point-of-use meters at fifteen minute intervals and tabulated in Fig. 6a the proportion of readings falling outside of the ANSI standard range of 0.95–1.05 pu. In general, voltages appear to be well-controlled, with most runs having less than 0.002% of readings out of range, and the worst case (R3-12.47-3, Sac.) having 0.32% of readings out of range. Voltage magnitude problems are most pronounced in Sacramento, which we attribute to Sacramento's larger PV penetrations by energy (see Appendix A.8) and relatively low minimum loads relative to peak; though penetrations by power capacity are the same, Sacramento has more hours with high PV production relative to demand.

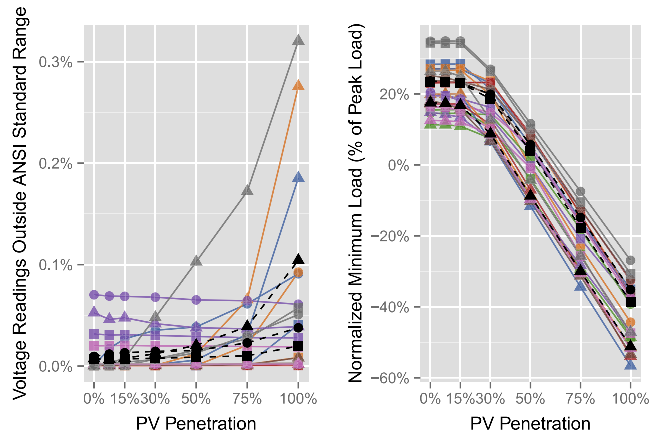
This finding – namely that voltage impacts are usually small – is consistent with prior work suggesting that many feeders can support high penetrations of PV without voltage violations (Hoke et al., 2013), however it may be counter-intuitive that feeders designed for one-way power flow can host so much PV capacity without more negative voltage impacts. There are several explanations for this. First, the feeders we investigated had relatively good voltage control and voltage regulators rarely saturated; it is plausible that there are feeders in operation whose control is more likely to saturate. Second, we did not model scenarios with PV heavily concentrated in part of a feeder – this would exacerbate local reverse power flow and voltage rise. Finally, though the maximum penetration we investigated is relatively high, penetrations could be on the order of 200% if systems were sized to produce as much energy over the course of a year as each building consumes. We expect that voltage excursions would be much more significant at those penetrations.

In general, the voltage violations that did occur took place on rural and suburban feeders (see Table 1) with violations being very rare on urban feeders at all penetration levels. Except at feeder R1-25.00-1, almost all out-of-range voltages observed were greater than 1.05 pu. As



(a) Tap changes. (b) Mean current duty.

Fig. 5. Line voltage regulator activity across all three phases. See Section 3.4 for discussion of broken lines.



(a) Proportion of voltages outside ANSI standards. (b) Annual minimum load.

Fig. 6. Voltage control and minimum load (representing the magnitude of reverse power flow). Many scenarios overlap near 0.0% in (a).

expected these high-side excursions generally become more frequent as penetration increased and the power injection from PV raised some voltages locally. At R1-25.00-1 the out of range voltages were predominantly less than 0.95 pu, with a small amount greater than 1.05 pu. Under these conditions, increasing PV penetration improved voltage quality on the feeder by boosting some local voltages that would otherwise be low. As noted in Section 3.4, it is possible that more brief voltage excursions would be observed with higher resolution PV generation data.

3.6. Reverse power flow

Fig. 6b shows the minimum load, as a fraction of peak demand, measured over the year of simulation on each feeder. Negative values indicate that the feeder experiences reverse power flow conditions. These results indicate that the amount of reverse power flow takes on a very large range across the feeders we investigated, and that Sacramento feeders experience the largest reverse power flow conditions. This result is due to the fact that Sacramento loads have larger peak to mid-day demand ratios (due to air conditioning loads peaking in the late afternoon or early evening); PV penetration is defined by peak demand but reverse power flow depends PV production and *mid-day* demand.

We also investigated the incidence of negative real power flow ("backflow") through the substation, which can be a proxy for protection issues and higher interconnection costs. At 50% penetration, twelve of the 24 scenarios exhibited occasional backflow, up to 1% of the time each. At 100% penetration, all scenarios experienced backflow at least 4% of the time. In general, backflow was more prevalent in Sacramento because PV penetration in Sacramento was measured against a higher peak air conditioning load. This led to a larger absolute quantity of PV generation in Sacramento but with similar low loads to Los Angeles and Berkeley on cooler days.

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3.7. Observations regarding geographic diversity

We ran our sensitivity scenarios primarily to assess the effect of PV profile time resolution and geographic diversity on voltage regulator operation (see Section 3.4). However, these scenarios enable us to observe how other outcomes vary with the input data as well. These observations are necessarily tentative because the sensitivities were run for only two feeders (R1-25.00-1 and R3-12.47-3) in one location (Los Angeles).

First, we note that for all outcomes observed, differences between the single-profile one-minute input and that input downsampled to fifteen-minute resolution were minimal. This implies that fifteen-minute PV data is "good enough" for a reliable study of PV's effects on the distribution system.

Second, for two metrics we did observe changes in outcomes when switching from the full geographic diversity of profiles to the single profile for all PV installations. First, peak load reduction was larger with geographic diversity than without it. We attribute this to the fact that the diverse set of profiles includes west-facing installations that are more effective at reducing peak load. We also noticed substantially less backflow at high penetrations with geographic diversity. This is expected because with a single profile periods of high generation will be completely coincident, whereas with a diverse set of profiles they will be spread out somewhat – by system orientation if not by cloud cover differences – reducing the overall "peakiness" of PV generation and thus backflow. Taken together, these observations suggest that studies that do not account for the geographic diversity of PV – even on a distribution feeder scale – may underestimate some of its benefits and/or overstate its drawbacks.

4. Concluding remarks

We studied how distributed PV impacts distribution systems across a variety of feeder architectures and climates within California over a full year of operation. In contrast to earlier studies, we ran simulations with real PV data (either 1-min or 15-min resolution), which allowed us to uniquely address issues of voltage regulation on the time scale of cloud transients. In addition to studying voltage excursions, resistive losses, reverse flow and impact on peak loading – as have researchers before us – we examined voltage regulator operation and loss of life in secondary transformers. We used unique PV data that captured the impacts of fast cloud transients, array shading and spatial diversity.

At a high level, our results indicate that at penetrations up to 100%, the impacts of PV production are generally small, with both positive (capacity benefits) and negative (voltage regulation) effects. However we do observe important variation in impacts across feeder types and locations that warrant further investigation.

It is worth emphasizing that, while this paper is extensive in terms of its combination of geographic scope, number of feeder types and high resolution PV data, it is not an exhaustive assessment of all possible outcomes. We expect that a similar pattern of observations would hold across an even larger range of California scenarios than we consider in this paper. However, though the taxonomy feeders are meant to be representative, the actual diversity of infrastructure is large enough that there are feeders which would experience more severe impacts from distributed PV (lower primary voltage systems, though relatively rare, are a likely case). In this sense we regard our results to be representative of typical feeders – but not an exhaustive representation of the possible range of impacts. The research community would benefit from similar analyses with additional feeder models in additional locations to generalize the results in this paper. There is also a need for additional measurement and verification in real feeders to understand how well model results reflect reality in these circumstances.

We also note that we have not studied measures to mitigate the observed impacts. For example, if one reconfigured a feeder with new conductors or voltage regulating equipment our results would no longer hold. There may be a number of relatively low cost modifications that distribution engineers could employ – for example additional voltage regulating equipment – that would improve feeder performance with respect to voltage excursions but increase mechanical switching events. Optimal modification of feeders to facilitate distributed PV hosting is an important area for future research.

A number of other researchers have investigated the impact of PV on resistive losses in simulated distribution systems (Quezada et al., 2006; Thomson and Infield, 2007; Navarro et al., 2013; Widén et al., 2010), with a very broad range of results (ranging from a large reduction in losses to an increase in losses). Our findings capture this range; consistent with Nguyen et al. (2015), we find that on most feeders resistive losses continue to decline up to 100% penetration. Other researchers have also investigated the incidence of voltage excursions in simulation studies, and as with resistive losses our results capture the range in the literature (Thomson and Infield, 2007; Navarro et al., 2013; Widén et al., 2010; Nguyen et al., 2015). However Nguyen et al. (2015) is the only paper we are aware of that investigates voltage impacts with fast time scale PV data. Our study confirms their result with many more hours of simulation and climates: though some feeders have an increase in voltage excursions, most do not. This suggests that, although there is a range of voltage effects, feeders in practice will respond relatively well to high PV penetrations.

However an important caveat is that we did not model PV penetrations beyond 100%. On the feeders we investigated this corresponds to between 50% and 65% penetration by energy; this suggests that penetrations by power could be as much as twice those we studied on a zero net energy feeder. At penetrations beyond those we investigated, we expect that: resistive losses would increase on most feeders, peak load benefits would diminish, voltage regulator operations would continue to increase, and voltage magnitude impacts would increase. Referring to Fig. 6a, which showed voltage magnitude problems increasing rapidly with penetration on the highest *energy* penetration, we believe that voltage magnitudes could become serious problems at higher penetrations, primarily as a result of increased reverse power flow.

One of the distinguishing features of this paper is that we have investigated a very broad range of feeder types and locations with relatively high temporal and spatial resolution PV data. This allows us to generalize our findings by investigating which factors – in particular feeder type and location – most strongly influence our results. The tendency of losses to begin increasing at high penetration appears to be driven by location, but feeder type has a stronger influence on the *total* reduction in resistive losses. As one might expect, we find that percent peak load reduction depends more on location (climate) than on feeder type. Similarly, reverse power flow depends more strongly on location than feeder type, and in general those locations with more reverse power flow are also those with more peak load reduction. Some feeder types have little to no change in voltage magnitude deviations with increasing PV penetration, while other feeders show an increase in voltage deviations; the worst deviations occur in the same location (Sacramento). We found that impacts on voltage regulators are small and can either increase or decrease relative to a no PV baseline, depending on feeder type (and independent of location).

Another unique aspect of our study was access to fast temporal resolution data from real PV systems. However we found that results changed negligibly when we downsampled one-minute resolution data to 15-min resolution. This suggests that for annual time scale studies such as ours, 15 min data may suffice. This may not hold for studies that examine large PV systems concentrated at a single location on a feeder (such as Nguyen et al. (2015)), because in that case the severity of short time scale fluctuations in voltage magnitude would likely increase.

Finally, we note that while changes in distribution planning are likely required as distributed generation increases, those changes may be required only on a small number of feeders. This is because impacts – both positive and negative – are relatively small in most cases we investigated. An important area of future research is to develop methods to identify ahead of time the locations and feeder types that will have difficulty integrating large amounts of distributed PV and to focus advanced planning on those.

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Appendix A. *A.1. Modeling software*

We used GridLAB-D version 2.3 (with the forward–backward sweep power flow solver) to model distribution circuits due to its integration of power flow analysis and time-varying load models, availability of representative feeder models, and open-source license. We used GridLAB-D's detailed load modeling capabilities for HVAC equipment (responsive to solar irradiance, outside air temperature and scheduled operation), residential water heating and pool pumps and commercial building lighting. All remaining load at each building follows unique aggregated patterns that reflect variable occupancy and equipment scheduling. Loads are modeled with detailed assumptions about power factor (see Appendix A.4) and ZIP load parameters; see (PNNL, 2015a) for additional detail. In this section we describe our preparation of the models and supporting data.

A.2. Feeder topologies

Pacific Northwest National Lab (PNNL) has compiled a set of representative "taxonomy" feeders drawn from utilities throughout the United States (Schneider et al., 2008). As summarized in Table 1, the feeders vary along a number of important dimensions such as loads served (urban vs. rural), peak loading, and physical length. The feeders are organized by climate region. For this work, we selected the eight feeders originating from region 1 (temperate west coast) and region 3 (desert southwest) as these climates dominate California.

A.3. Locations and timeframe

We simulated each of the eight feeders in three locations – Berkeley, Los Angeles and Sacramento – during the 366 days between September 25, 2011 and September 24, 2012, inclusive. We chose these locations and time span due to the availability of high-resolution PV generation and weather data. See Appendicies A.5, A.6, A.7 for more on this data and feeder placement. Note that the California peak demand during the selected year was fairly typical relative to the past decade, with a peak load of 46,846 MW in 2012 versus a high of 50,270 MW in 2006 (CAISO, 2013b). This means that the simulations do not include extreme conditions that may affect PV's overall value in important ways in the long run.

A.4. Feeder loads and power factors

Because the taxonomy feeders specify only static planning (i.e. peak) loads, PNNL provides a script to populate the feeders with time-varying residential and commercial loads (PNNL, 2012). Details of the loading process are discussed in detail in Sections 2.2–2.4 of Schneider et al. (2010); we limit the discussion here to a few points of relevance.

The PNNL method models end-use loads with "house" objects that have a weather-dependent HVAC component and schedules for other types of loads such as appliances. The schedules for each house are scaled and time-shifted to provide heterogeneity among loads. Commercial loads are modeled as groups of "houses" with a different set of load schedules corresponding to commercial activities.

The PNNL script applies a different distribution of load types depending on the climate region selected; e.g. air conditioning is more common in region 3 than in region 1. In this study, we applied region 3 loads to Los Angeles and Sacramento simulations and used region 1 loads in Berkeley, in keeping with the actual climate zone location of these cities.

Referring to the literature (Schneider et al., 2010; Shoults and Swift, 2012; Bravo, 2012), we adjusted the script-default load power factors as summarized in Table A.2. We also reduced a capacitor bank on one feeder (R1-25.00-1) from 150 kvar/phase to 50 kvar/phase after noticing that it was overcompensating for reactive power, possibly because it is a rural feeder and is meant to handle more pumping load.

A.5. PV generation data

The PV integrator SolarCity provided us with a database of instantaneous power at each inverter they monitor (roughly 7000 systems, mostly in California) under the terms of a non-disclosure agreement. All the inverters are single phase and provide data on the quarter hour; for this project SolarCity also sampled a number of inverters at the fastest available time step of one minute.

We performed data quality filtering to ensure we used only complete and credible profiles in the models. To address remaining missing readings in the selected profiles, we chose a very complete profile (with at least 365.8 days of non-zero readings between 8:00 and 16:00) from near the center of each location. We used readings from these "filler" profiles to fill gaps longer than one hour in other profiles from that location, scaling the filler readings by the ratio of the two profiles' rated capacity. Any shorter gaps we allowed to be handled internally by GridLAB-D, which uses the last-seen generation value until the model clock reaches the timestamp of the next reading.

A.6. Weather data

Table A.3 summarizes the weather data we used in this study. We obtained one-minute temperature, humidity, and solar irradiance data for Berkeley from Lawrence Berkeley National Laboratory (Fernandes, 2012) and for Los Angeles and Sacramento from SOLRMAP at Loyola Marymount University and Sacramento Municipal Utility District (NREL, 2012). The Los Angeles and Sacramento data, having been quality controlled at the source, appeared to be quite complete and reliable and was used with only minor reformatting.

The Berkeley data required the following edits: We calculated direct solar irradiance from global and diffuse irradiance using the solar zenith angle. Also, when irradiance data were missing or zero during the daytime, if less than an hour of data were missing we interpolated between adjacent values (for a total of 30 h). For longer gaps (totaling 37.4 days) we copied in data from nearby days with similar cloud conditions as measured at Oakland Airport, 18 km (11 mi) south (NOAA, 2013). We also filled sub-hourly gaps in temperature data (totaling 5.5 days) by interpolation and longer gaps (totaling 25.6 days) directly with hourly measurements from Oakland Airport.

The temperature, humidity and irradiance data determined HVAC load in GridLAB-D but were not used to simulate PV generation, which was instead extracted from the SolarCity database. By using generation data sources located not far from the weather stations we preserved some (if not all) of the correlation between air conditioning load and PV generation. Given that buildings have significant thermal mass (resulting in a lagged and smoothed response to weather) and our goal was to preserve broad correlations between PV output and building load, we believe that the necessary corrections to the Berkeley weather data are acceptable and do not substantially affect the results.

A.7. Geographic assignment of PV profiles

We sought to attach PV profiles to GridLAB-D houses in a way that reflects the diversity of solar generation over the area of a distribution feeder. This geographic diversity is driven in part by variations in cloud cover, but also by differences in PV system orientation, technology and shading – all of which are reflected in the SolarCity data set.

The GridLAB-D taxonomy feeders are anonymized and therefore we do not know their physical layout. However, the models do contain electrical connectivity for all components and lengths for each overhead and underground line segment. We used this information and the graph layout utility Graphviz to create a geographic layout for each feeder subject to these constraints. These layouts are available online (Cohen, 2013).

Table A.2
Power factors by load type.

HVAC		Residential		Commercial	
Base HVAC	0.97	Water heater	1.0	Int. lights[a]	0.90
Fans	0.96	Pool pump[a]	0.87	Ext. lights[a]	0.95
Motor losses	0.125	Other res.[a]	0.95	Plug loads[a]	0.95
				Street lights	1.0

[a] Power factor was changed from the PNNL default value of 1.0.

Table A.3
Location characteristics.

Location	Temp (°C)			Temp (°F)			PV profiles used	Max distance of PV site from weather station
	Low	Mean	High	Low	Mean	High		
Berkeley	0	13	35	32	56	94	97	39 km (24 mi)
Los Angeles	4	17	34	39	62	94	99	27 km (16 mi)
Sacramento	−4	16	43	25	61	109	101	45 km (28 mi)

We then used ArcGIS to superimpose the resulting feeder layouts on the SolarCity profile sources. We manually placed the feeders in locations with high densities of generation profiles to capture as much spatial diversity as possible. We then ran a "nearest neighbor" query to assign each distribution transformer to the closest SolarCity profile with acceptable data quality. As Table A.3 shows, at each location roughly 100 profiles were used (that is, matched with a transformer) with at least one feeder. Table 1 breaks down the number of profiles used in each individual scenario.

A.8. Penetration levels and PV placement

For each GridLAB-D run, we populated only a portion of the houses with PV, to test various levels of penetration. To define "penetration" we first needed to establish a baseline loading for each feeder. To this end, we executed a baseline run for each feeder (with no PV) in each location and recorded its peak load. We then defined penetration as:

$$\text{PV penetration} = \frac{\sum(\text{PV system ratings})}{\text{Peak feeder load from baseline run}}$$

We tested PV penetration levels of 0%, 7.5% 15%, 30%, 50%, 75% and 100%. We placed PV randomly across the available house models and used the same random number seed for all scenarios. Using the same seed ensured that PV was placed at houses in the same order for each climate (Berkeley, Sacramento, Los Angeles), and that all systems populated in lower penetration runs were also populated in higher penetration runs. This allowed us to make comparisons across climates and penetration levels. We modeled the PV as a unity power factor "negative load". Each house's PV generation followed the time-varying load profile associated with its distribution transformer (as described in Appendix A.7), scaled to an appropriate size for the building as described in Appendix A.9. Because GridLAB-D simulates three phase power flow and we randomly assigned PV systems to single phase points in the system, we are naturally capturing any phase imbalances that would occur from distributed PV in the specific case of random placement. To the extent these imbalances influence voltage magnitudes, they influence our results in Sections 3.4 and 3.5.

Fig. A.7 shows PV energy penetration as a function of PV capacity. Variation in the ratio of energy to power capacity is driven primarily by variation in load factor (average demand divided by peak demand) which in turn is driven by variation in climate and load composition.

All penetration levels should be treated as approximate for two reasons. First, our denominator for penetration was the baseline peak load during the test year, rather than the long-run feeder peak load which would typically be used in situations where more data was available. Second, due to transformer scaling (see Appendix A.10) and other minor adjustments, the peak loads from the final 0% penetration runs differ slightly from the peak loads of our baseline runs. In general this difference is small, with the 0% penetration runs having peak load ranging between 3.9% lower and 2.9% higher than the baseline runs. However, in one scenario (R1-12.47-3, Berk.) the final peak load was 8.0% lower than the baseline peak load. So in this worst case scenario the nominal 100% penetration might more accurately be read as a 108.7% penetration.

A.9. PV generation profile scaling

All of the selected PV generation profiles appear to be residential-scale, with system ratings ranging from 1.68 kW to 13.16 kW. To establish a reasonable installation capacity for each building, we first used the following formula from PNNL's load population script (PNNL, 2012):

$$\text{building PV rating estimate} = A \times 0.2 \times 92.902$$

where A is the floor area of the building in square feet, 0.2 is a rough estimate of the rated efficiency of the installations, and 92.902 W/ft^2 is the "standard test conditions" insolation.

We scaled up all commercial PV generation profiles so that their ratings matched this rating estimate. For residential installations, we scaled down the generation profile if its

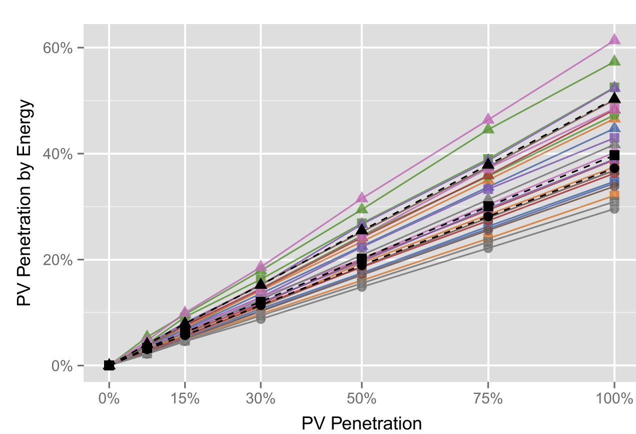

Fig. A.7. PV energy penetration as a function of penetration by capacity.

rating was *higher* than the rating estimate for the house. We did not scale up residential profiles with ratings smaller than the rating estimate since it is common for residential installations not to occupy the entire roof space. We note that we did not simulate the effect of even larger standalone "utility scale" (multi-MW) PV systems. Had we done so, we expect that voltage and reverse flow problems would be more severe than those we present in Sections 3.5 and 3.6.

A.10. Transformer scaling

Transformer aging is one of our outcomes of interest, and it depends not on absolute loading of the transformer but loading relative to the transformer's rating (IEEE, 1996). While the simulated loads are roughly scaled to the planning load value listed at each transformer in the taxonomy feeders, the loads may be somewhat larger or smaller than the planning loads due, for instance, to our use of different weather data at the three locations. This means that, unless corrected, some transformers would be sized inappropriately for the loads attached to them.

To address this issue, we assembled a "menu" of distribution transformers in standard kVA sizes based on the units present in the taxonomy feeders and manufacturers' data (General Electric, 1972; ABB, 2001). We then replaced each transformer with the smallest transformer from the menu with a rating greater than the observed peak apparent power for that transformer from the baseline run. This is a conservative size estimate for distribution transformers given that in practice many carry power over their ratings during peak periods (IEEE, 1996).

Note that to some extent the concern about transformer sizing also applies to conductor sizing; some taxonomy feeder line conductors may not be sized appropriately for the simulated loads. Because conductor sizing was not a focus of this work, we did not undertake to resize the conductors in the way we did the transformers, and indeed when we run GridLAB-D we occasionally observe warnings that conductors are modestly overloaded. This may slightly distort the absolute results for line losses. To address this we instead report the percent change in losses between penetration scenarios. The percent change should not be affected significantly by conductor size since line resistance is a linear scaling factor on line losses and all penetration levels use the same conductors.

A.11. GridLAB-D configuration

All of the taxonomy feeders have an on-load tap changer (LTC) at the substation, and two of them feature additional line voltage regulators. During the baseline runs, we observed that the upper bound of the LTC and regulator deadbands were set at approximately 1.05 pu, right at the edge of ANSI standards for end-use voltages. This contributed to a significant number of voltage violations due to time lag in regulator response when voltages rose outside the deadband. We therefore lowered the top of the LTC and regulator deadbands to 1.04 pu (maintaining the bandwidth) for our production model runs. The controller deadband is ± 0.008 pu on all voltage regulators and LTCs.

GridLAB-D runs with an adaptive time step, meaning that it runs the power flow solver only when an input to the model (such as weather or PV production) changes or a simulated element within the model is expected to change (for example a building model). As described above, the PV data we used were sampled at most once per minute, and we used 1 min resolution weather data. Because the data inputs change no more than once per minute, simulated voltage regulating equipment will not change position more than once per minute. Therefore to contain run time we set the minimum simulation time step to 1 min. We note that in practice voltage regulating equipment may have shorter delay times (e.g. 30 s); as we address in the results section (Section 3.4), we believe that limiting the time step to 1 min does not significantly affect the results.

See (PNNL, 2015b) for additional detail about GridLAB-D configurations.

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