Endogenous Assessment of the Capacity Value of Solar PV in Generation Investment Planning Studies

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August 2015

Accepted pre-print manuscript reprinted with permission from IEEE Transactions on Sustainable Energy

https://doi.org/10.1109/TSTE.2015.2456019

This work was supported by the U.S. Department of Energy (DOE) Solar Energy Technologies Office as part of the DOE SunShot Initiative under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

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Francisco D. Munoz, *Member, IEEE,* and Andrew D. Mills

Abstract

There exist several different reliability- and approximation-based methods to determine the contribution of solar resources towards resource adequacy. However, most of these approaches require knowing in advance the installed capacities of both conventional and solar generators. This is a complication since generator capacities are actually decision variables in capacity planning studies. In this article we study the effect of time resolution and solar PV penetration using a planning model that accounts for the full distribution of generator outages and solar resource variability. We also describe a modification of a standard deterministic planning model that enforces a resource adequacy target through a reserve margin constraint. Our numerical experiments show that at least 50 days worth of data are necessary to approximate the results of the full-resolution model with a maximum error of 2.5% on costs and capacity. We also show that the amount of displaced capacity of conventional generation decreases rapidly as the penetration of solar PV increases. We find that using an exogenously defined and constant capacity value based on time-series data can yield relatively accurate results for small penetration levels. For higher penetration levels, the modified deterministic planning model better captures avoided costs and the decreasing value of solar PV.

Index Terms

Capacity Value, Solar, Generation Planning, Approximation Techniques, Installed Reserve Margin.

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This research was funded by the U.S. Department of Energy (DOE) Solar Energy Technologies Office as part of the DOE SunShot Initiative and CONICYT/FONDAP/15110019 (SERC-CHILE). Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under Contract DE-AC04-94-AL85000. This manuscript has been authored by an author at Lawrence Berkeley National Laboratory under Contract No. DE-AC02-05CH11231 with the U.S. Department of Energy.

NOMENCLATURE

Sets and Indexes:

G	Set of conventional generators, indexed g
H	Set of hours, indexed h
$S(X)$	Set of outage scenarios, indexed s

Parameters:

AV_{ghs}	Generator availability
CAP_g	Nominal capacity of generator [MW]
CC_g	Annualized capital cost of generator [$/MW-year]
CPV	Capacity value of solar PV [MW]
D_h	Demand level [MW]
D_{h^*}	Peak demand [MW]
EUE	Threshold of expected unserved energy, expressed as a percentage of total demand
FOR_g	Generator forced outage rate
MC_g	Marginal cost of generator [$/MWh]
ND_h	Demand less solar PV output [MW]
P_s	Probability of outage scenario
PV_h	Solar PV output [MW]
RM	Installed reserve margin

Variables:

u_{hs}	Amount of unserved energy [MW]
x_g	Generation investment decision (binary)
y_{ghs}	Generation dispatch level [MW]
X	Vector of investment decisions, x_g

I. INTRODUCTION

Significant reductions in the price of solar generation technologies increasingly make it a viable economic alternative to supply power at competitive prices [1], to offset greenhouse gas emissions [2], and to meet renewable targets at minimum cost for consumers [3], [4]. Advancements in the last decades have reduced the installed price of small solar PV systems from approximately $12 per W in 1998 to less than $5 per W in 2013 [5], and projections indicated further reductions in the near future [6]. Installed solar capacity in the U.S. now exceeds 15 GW and, due primarily to growth in utility-scale PV, is expected to exceed 20 GW by 2016 [7].

Decisions by load-serving entities (LSEs) regarding the selection of resource portfolios to meet forecasted demand, to maintain the reliability of the system, and to fulfill policy objectives can be complex. Weighing one option over another involves consideration of several attributes that determine the economic value of a resource to the overall

system [8]. Our focus in this article is the contribution of solar PV (and other variable energy resources such as wind) to resource adequacy requirements as part of these broader resource planning decisions.

Several methods can be used to assess the capacity value of variable energy resources—primarily solar and wind generation technologies. Probabilistic methods are among the most accepted because they rely on standard metrics such as the loss of load expectation (LOLE) or the expected unserved energy (EUE) [9]. A popular approach is the computation of Effective Load Carrying Capability (ELCC), which provides a measure of the amount by which demand could be increased after adding a generator while maintaining the same reliability level [10]. Other reliability-based metrics include the Equivalent Conventional Power (ECP) and the Equivalent Firm Power (EFP), but these are rarely used in practice [11]. Although these metrics can provide very accurate measures of the capacity value of renewable generators, they require extensive amounts of system data and can be computationally difficult to evaluate.

Approximation methods, on the other hand, can provide relatively good estimates of the capacity value of time-dependent renewable energy technologies at a much lower computational cost. Some approximation approaches aim at providing direct estimates of the ELCC (e.g., Garver's method [12], an extension of Garver's approach to multi-state capacity representation of power plants [13], and the Z method [14]). Other approximation methods base calculations on the availability of solar or wind resources during risky periods, such as peak load. Milligan and Parsons [15], for instance, propose approximating the capacity value of wind by computing the LOLP-weighted sum of hourly capacity factors over a subset of peak-load hours. An even simpler method that is used by several ISOs in the U.S. is to average the capacity factor of a generator over, say, the top of 10% load hours [10]. Milligan and Parsons [15] find that for wind, these approximations based on time-dependent data provide sufficiently accurate results. Recent surveys on probabilistic- and approximation-based methods to calculate the capacity value of wind are in [16]–[19]. Madaeni et al. [11] compare the performance of approximation methods to reliability-based approaches for solar PV and also conclude that capacity factor-based metrics give good estimates of the capacity value for this technology. However, they point out that due to the high correlation between load and solar irradiance, setting a low threshold of peak hours (e.g., less than top 30%) can result in underestimation of the capacity value of PV. Furthermore, as we will show, at least some of the approximation methods (i.e., capacity factor during peak load hours) become increasingly inaccurate with higher penetrations, as generation during "net" peak load hours becomes increasingly important.

An important limitation of these methods is that the installed capacities of all generators need to be known in advance. It is challenging to identify the optimal portfolio of resources if this has to be specified in order to estimate contributions to adequacy. Instead, ELCC is estimated for one technology at a time which foregoes the opportunity to investigate portfolio interactions when multiple resources are changed.

An alternative to determining the capacity contribution of one resource at a time is to establish a portfolio-wide reliability target, such as LOLE or EUE, and find the optimal mix of resources that meet the constraint. Examples of capacity expansion models with such capabilities include the algorithms described in [20] and in [21], which are now part of the EGEAS model managed by the EPRI [22]. More recent developments of capacity expansion

models with probabilistic production cost simulations include [23] and [24]. These capacity expansion tools find the optimal portfolio of generation investments that minimize capital and operating costs subject to a constraint on the maximum amount of expected unserved energy. By considering both production costs and the full space of outages, the contribution of solar or wind towards resource adequacy is done endogenously, without the need for computing reliability metrics such as the ELCC. However, this model has not been used in the past to study the effect of different penetration levels of solar or wind on their capacity value for the system.

In this article we make the following contributions:

- First, we examine the contribution of solar PV (and wind) to resource adequacy using a probabilistic capacity expansion model that uses a portfolio-wide EUE constraint.
- Second, we compare the results of the probabilistic model to two deterministic-based planning models. One is a standard capacity-planning model that enforces installed reserves with respect to the peak demand. The other one is a simple alternative that we propose to endogenously represent the capacity contribution of solar PV (and wind) without the full probabilistic simulation.
- Third, we study the effect of using samples of representative dispatch conditions of varying sizes in the probabilistic capacity planning model.

We introduce these models in Section II and describe the data used in a case study in Section III. In Section IV we evaluate the impact of using a sample of all available days in the dataset. We then use the models to estimate the capacity contribution of solar PV (and wind) and find the avoided cost associated with adding these resources to the portfolio. Finally, we conclude with the specific contributions in Section V.

II. Capacity expansion models

In this section we describe the probabilistic capacity expansion model used with our case study. This model minimizes total system cost subject to a reliability constraint and considers the full space of generator outage possibilities. We then describe a standard deterministic capacity expansion model that enforces resource adequacy through an installed reserve margin constraint. We introduce a variation to this approach we call the virtual demand curtailment (VDC) model that endogenously represents the capacity contribution of solar PV (and wind). In all cases the objective is to minimize the sum of the annualized capital cost and operations for a representative year. For analysis purposes we specify the installed capacity of solar PV in each case. However, the capacity expansion models could be extended to account for different investment alternatives in wind, solar, or hydro technologies. Examples of such implementations are in [25]–[28].

For the sake of simplicity, we ignore ramping constraints, unit commitment variables/constraints, and transmission limits. Although it has been shown that relaxing unit commitment constraints could result in biased generation investment portfolios [29]–[32], the changes in cost and generation portfolio that results from considering these

additional variables and constraints are rather small [33].[1] Moreover, transmission limits are often accounted for in resource adequacy studies through the definition of reliability areas within decongested regions. Thus, we believe that the impact of relaxing unit commitment variables and transmission limits in our analyses does not affect our conclusions. However, there are two simplifications that could potentially affect the optimal generation investment portfolio. One of them is the relaxation of ramping limits, which become important at high penetration levels of solar PV due to the larger magnitude of extreme ramp events in the early evening and, therefore, the need for a more flexible fleet of conventional generators.[2] The second one is consideration of operating reserves and maintenance schedules for generators.[3] However, studying the impact of these features on the capacity value of solar PV is beyond the scope and we leave it as a subject of future research.

A. Probabilistic model

To investigate capacity expansion decisions with solar PV we use a benchmark probabilistic model that fully accounts for forced outages in conventional generation and variability in demand and solar PV. Variability in demand and PV is accounted for through hourly profiles from historical data. The objective of the probabilistic model (Equation (1)) is to minimize the sum of the annualized cost of investments in conventional generation and the expected costs of dispatching those investments to meet net demand. We allow for spillage of power from solar PV if $PV_h > D_h$ and define the net demand as $ND_h = max\{D_h - PV_h, 0\}$.

$$min \sum_{g \in G} CC_g x_g + \sum_{s \in S(X)} P_s(X) \sum_{g \in G} MC_g y_{ghs} \tag{1}$$

Subject to constraints:

$$\sum_{g \in G} y_{ghs} + u_{hs} = ND_h \quad \forall h \in H, s \in S(x) \tag{2}$$

$$y_{ghs} \leq AV_{ghs}(X) CAP_g x_g \quad \forall g \in G, h \in H, s \in S(x) \tag{3}$$

$$\sum_{s \in S(X)} P_s(X) \sum_{h \in H} u_{hs} \leq EUE \sum_{h \in H} D_h \tag{4}$$

$$x_g \in \{0, 1\} \quad \forall g \in G \tag{5}$$

$$y_{ghs}, u_{hs} \geq 0 \quad \forall g \in G, h \in H, s \in S(X) \tag{6}$$

[1]Jin et al [33] find that the generation investment portfolio found using a simple economic dispatch model differs from the one found using a detailed unit commitment simulation. However, the performance of the solution found using the economic-dispatch based model is only 0.02% more expensive relative to the one found using the unit-commitment based capacity expansion model. Additionally, Palmintier [34] finds that it is possible to approximate the solution of a planning model with unit commitment constraints and variables to a high degree of accuracy by simply solving its LP relaxation.

[2]The California ISO projects that the total capacity of variable energy resources (i.e., solar PV, solar thermal, distributed PV, and wind) will be 15,701 MW in 2016. This will result in an increment of system maximum 3-hour net-load ramps from 7,654 MW in 2012 to 10,190 MW in 2016. Solar resources will be the largest contributors (52%) to maximum 3-hour continuous net-load ramps in the evenings of the non-summer months in 2016 [35].

[3]Palmintier [34] concludes that operating reserves and maintenance schedules are the two constraints from detailed production cost models that have the largest impact on the optimal portfolio selection in capacity planning models.

The outage space $S(X)$ depends on the vector of investment decisions $X = [x_1, x_2, ..., x_{|G|}]$ and defines all the possible combinations of generator availabilities[4] for the units that have been selected for construction (i.e., $AV(X)_{gs} = 0$ if $x_g = 0$). Thus, for a given X, the probabilities of each scenario are defined as follows.

$$P(X)_s = \prod_{g \in G} (1 - AV_{gs}(X))FOR_g + AV_{gs}(X)(1 - FOR_g) \tag{7}$$

Constraint (4) requires the expected unserved energy, which occurs when the generation capacity that is not on outage is less than the net demand, to remain below a chosen threshold. In addition, constraint (3) imposes a limit on the dispatch level from any unit, which must be less than its capacity if the unit is available (i.e., $AV_{gs}(X) = 1$), or equal to zero if the unit is on outage (i.e., $AV_{gs}(X) = 0$).

Fully evaluating the previously described problem is exceedingly challenging for realistic numbers of generators as the number of possible combinations of outages grows exponentially.[5] Various methods have been developed to reduce the complexity of the probabilistic production cost problem included in the investment planning model without sacrificing accuracy. These include the convolution of equivalent load duration curves through the Baleriaux-Booth method [36], [37], Monte Carlo simulations [38], and bounding techniques [39], among others [40], [41].

Bloom [20] proves that the model described by equations (1)-(6) can be separated into an investment problem (master problem) and a dispatch problem (subproblem) and solved to optimality using Benders decomposition. The dispatch problem accounts for all combinations of forced outages through the Baleriaux-Booth probabilistic simulation method [36], [37]. Duals from the dispatch problem with a candidate set of investment decisions are then passed to the investment problem to identify candidate investments that further reduce costs (i.e., an optimality cut) or bring the reliability level closer to the target level (i.e., a feasibility cut).

We implement Bloom's method to solve the probabilistic model to optimality. This model is our benchmark since it fully accounts for all possible combinations of forced outages when making investment decisions and estimating the operating cost of those units. In addition to the Bloom method for finding optimal generation investment decisions, we also employ standard methods for evaluating hourly unmet energy and Expected Unserved Energy (EUE) (as detailed by Fockens et al [42]), or Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE) (as detailed in Billinton and Allan [9]).

B. Deterministic model

In many instances the enumeration of forced outages in the probabilistic model introduces too much complexity for typical capacity expansion decisions, especially when considering transmission constraints. A standard approximation method is the use of a deterministic economic dispatch problem. Deterministic planning models enforce reliability requirements through an installed reserve margin constraint and derate the capacities of conventional

[4]In this article we assume that there are no derated states (i.e., $AV(X)_{gs} \in \{0, 1\} \forall s \in S(X), g \in G$).

[5]For instance, on a system with 100 generators there exist 2^{100} outage scenarios on each dispatch hour considered in the capacity expansion model.

generators based on their forced outage rates [43]. Examples of planning models that utilize these approximations are described in [27], [43]–[52].

We formulate the deterministic planning model as follows.

$$min \sum_{g \in G} CC_g x_g + \sum_{g \in G} MC_g y_{gh} \tag{8}$$

Subject to constraints:

$$\sum_{g \in G} y_{ghs} = ND_h \quad \forall h \in H \tag{9}$$

$$y_{ghs} \leq (1 - FOR_g) CAP_g x_g \quad \forall g \in G, h \in H \tag{10}$$

$$\sum_{g \in G} CAP_g x_g + CPV \geq (1 + RM) D_{h^*} \tag{11}$$

$$x_g \in \{0, 1\} \quad \forall g \in G \tag{12}$$

$$y_{ghs} \geq 0 \quad \forall g \in G, h \in H \tag{13}$$

Note that in constraint (10) the capacity of generators is derated in proportion to the expression $1 - FOR_g$, as in [43]. Constraint (11) enforces an installed reserve margin RM with respect to the peak demand, D_{h^*}. The capacity of all conventional generators counts 100% towards this reserve margin. However, only a fraction of the installed capacity of solar PV, denoted CPV, counts towards the reserve requirement. The evaluation of CPV, which is often replaced by the estimate of the ELCC, is nontrivial for two reasons. First, the capacity value of solar decreases rapidly and nonlinearly as penetration increases [53]–[55]. Second, even if the capacity of solar PV is known in advance, evaluating the ELCC for the resource requires knowledge of the capacities of all conventional generators (i.e., knowing the vector X), which are actually variables in capacity expansion studies.

Existing deterministic capacity expansion models and resource adequacy studies use different assumptions to account for the deterioration of the capacity value of solar at higher penetration levels [8], [56]. Some ISOs use a constant pre-determined value to determine capacity payments for all new solar resources; this pre-determined value only considers generation during peak demand periods, rather than peak net demand [8], [57]. Focusing only on generation during peak demand periods leads to calculated capacity value staying constant with increased penetration. This is the same simplification used in the capacity expansion models IPM [46] and PLEXOS LT [49]. Other models account for the variation in the capacity value of solar indirectly by, for instance, a requirement of backup conventional generation that changes with penetration levels [58]. However, the capacity value of solar in all of these models and studies is exogenously defined, which could over or underestimate the need for firm capacity to meet resource adequacy targets. A potentially better approximation is the one used in the ReEDS model [59]. Since ReEDS is solved sequentially, using a rolling horizon, the model computes the updated estimates of the average and marginal capacity contributions of solar and wind generation technologies *in between* periods. Nevertheless, since the parameters used *within* periods are constant and do not depend on the investment variables, it is not clear whether such approximation will provide the right economic signals for large additions of time-dependent renewable energy technologies, particularly solar PV.

C. Virtual Demand Curtailment model

A trivial modification to the installed reserves constraint (11) is to enforce the reserve margin requirements with respect to the peak net demand. This approach is used in the SWITCH-WECC model [60] and it does not require the specification of a value (or function) CPV for the capacity value of solar. Since the peak net demand is not necessarily known in advance–if the installed capacity of solar PV is variable–this modification requires enforcing the installed reserve margin on an hourly basis. Here we enhance this formulation by adding variables v_h that allow for small violations to the modified installed reserve constraint (15).

$$\sum_{g \in G} CAP_g x_g \geq (1 + RM)(ND_h - v_h) \quad \forall h \in H \tag{14}$$

$$\sum_{h \in H} v_h \leq \delta \sum_{h \in H} D_h \tag{15}$$

The v_h variables can be interpreted as virtual demand curtailments. We control the maximum amount of virtual curtailment through the parameter δ on equation (15), which is comparable to the expected unserved energy constraint (4) in the probabilistic model. The value of δ is, however, chosen independently of the EUE target used in the probabilistic model. The reasons we introduce these relaxation parameters into the modified installed reserves constraints are a) to attempt to capture the capacity contributions of solar PV outside of the very peak net demand hour and b) to prevent low-probability events from imposing too conservative minimum required investment levels in conventional generation.

One of the main limitations of the method used in the SWITCH model [60] ($\delta = 0$) is that, in the end, only one of the constraints defined by (14) will be binding: the hour of peak net demand (h^*). This means that in the SWITCH model, the only factor determining the amount of installed reserves in the model that accounts for solar PV generation is the peak net demand (ND_{h^*}), therefore ignoring the contribution of solar PV towards meeting demand and, indirectly, towards resource adequacy of all near- and off-peak net demand hours. As we will show in the numerical experiments, a value of δ equal or close to zero will only allow the model to relax constraints (14) in a small neighborhood of the peak net demand, which will result in underestimation of the capacity value of solar PV for high penetration levels. On the contrary, using a large value of δ might allow the model to "put more weight" on a broader neighborhood of the peak net demand hours, but at the risk of underestimating the capacity value of solar PV for small penetration levels. Additionally, not relaxing constraints (14) can result in a model that is extremely sensitive to the selection of representative dispatch hours. For instance, if the parameter δ is set to zero, as in [60], a cloudy day in the dataset could drive excessive investments in conventional generation. In that situation the model will be "blind" with respect to the contribution of solar PV towards resource adequacy if a) in that given day and hour h^* the solar output is zero (P$V_{h^*} = 0$), b) the peak net demand equals the peak demand ($ND_{h^*} = D_{h^*}$), and c) that demand level happened to be the peak demand for the whole dataset ($D_{h^*} > D_h$).

In summary, the virtual demand curtailment (VDC) model aims at approximating the behavior of the probabilistic model by replacing the installed reserves constraint (11) from the deterministic planning model with the modified

installed reserve constraint (14) and the maximum virtual demand curtailment constraint (15). Although we find that it is possible to partially replicate the results of the probabilistic model for certain combination of parameters, we want to highlight that the VDC is only a heuristic approximation method that does not replace a full probabilistic investment-planning model.

III. Test-Case and Data

For the conventional generation investment options we use the 32 generators described in the IEEE Reliability Test System [9], which total 3,405 MW of potential generation capacity. Investment cost and operating costs were updated to reflect current estimates based on EIA data (see Table I). All of the resulting investment options are summarized in Table II. We computed the annualized investment cost for each technology as the sum of the overnight cost plus the present worth of fixed annual O&M costs for the lifetime of the asset.

TABLE I
Cost assumptions based on EIA data

Type	Overnight Cost [$M/MW]	O&M Cost [$/MW-yr]	Var. O&M [$/MWh]	Lifetime
Gas/CCGT	0.92	13,170	49.1	30
Gas/CT	0.68	7,040	82	30
Hydro	2.94	14,130	6.4	60
Coal/Steam	4.40	62,250	31.7	60
Nuclear	5.53	93,280	11.8	60

TABLE II
Conventional generation investment options

Name	Type	Unit Count	Unit Size [MW]	FOR	Var. Cost [$/MWh]	Ann. Inv. Cost [$M/yr]
U12	Gas/CCGT	5	12	0.02	49.1	0.87
U20	Gas/CT	4	20	0.10	82.0	1.02
U50	Hydro	6	50	0.01	6.4	8.46
U76	Coal/Steam	4	76	0.02	31.7	22.39
U100	Gas/CCGT	3	100	0.04	49.1	7.28
U155	Coal/Steam	4	155	0.04	31.7	45.67
U197	Gas/CCGT	3	197	0.05	49.1	14.34
U350	Coal/Steam	1	350	0.08	31.7	103.14
U400	Nuclear	2	400	0.12	11.8	154.16

We developed an hourly dataset of load, PV and wind generation based on information available for Arizona Public Service. Historical hourly loads were collected from Ventyx Velocity Suite [61]. Inter-annual load growth trends

were removed from the data by projecting all years to 2012 based on the long-term growth trends. The remaining load data still has inter-annual variation due to weather and other factors, but not due to long-term load growth. Historical solar generation was estimated through historical satellite observations in the National Solar Radiation Database (NSRDB) [62]. The satellite data was converted to PV production data using the NREL PVWatts model [63] assuming an AC to DC derate factor of 0.83. The individual sites and orientation of PV (azimuth, tracking/flat, etc) were based on previous information collected from APS [64]. Based on the available load and PV data we were able to create a time-synchronized dataset that covers seven years: 2003-2009. We also created a time series of wind data based on a set of 30 MW wind sites in the Western Wind and Solar Integration Study (WWSIS) dataset for 2004-2006 [65]. For the remaining years we repeated the 2004-2006 wind dataset. As a result the wind data is not fully time synchronous with the load and PV data over the seven year period, though wind is not the primary focus of our analysis and comparison of key correlation statistics between the synchronous (2004-06) and non-synchronous periods (2003, 2007-09) suggests our results will not be greatly skewed.

We scale the load data such that the peak load hour over the full seven year period is equal to 1500 MW. We assume that there is no installed generation in the system prior to solving the capacity expansion models. With these assumptions, choosing to build roughly half of the generation investment options in the IEEE RTS would meet this peak demand. In our parametric analyses in the next section, solar PV (or wind capacity) is an input to the model; however, solar PV (or wind) capacity could also be defined as a variable and determined endogenously if we instead incentivized investments on these technologies using production tax credits or environmental constraints.[6]

IV. Results

In this section we summarize the results from a range of numerical experiments using the probabilistic, deterministic, and VDC planning models. In Section IV-A we study the accuracy of two hour selection algorithms. In Section IV-B we compute the contribution of solar PV towards resource adequacy using the probabilistic model, the VDC model, and a capacity-factor based approach. Section IV-C discusses the implications of the decreasing marginal capacity contribution of solar PV. Section IV-D describes the reduction in utility costs as a function of solar PV penetration and highlights the importance of using a model capable of computing the capacity of the resource endogenously. Throughout Sections IV-C - IV-D we also display results for a wind site as a point of comparison to the results with solar PV. Finally, in Section IV-F we discuss the computational performance of the different planning models.

A. Comparison of hour selection methods

For all models, the computational burden increases with the length of the load, PV, and wind data. Here we investigate two approaches for reducing the length of the time series: daily sampling and clustering.

[6]Examples of investment planning models that account for Renewable Portfolio Standard constraints are in [27] and in [48]. Their implementation is, however, beyond the scope of this research.

The daily sampling algorithm selects a sample of days that minimizes the sum of the square differences of the means, standard deviations, and correlations between the sampled days and the full dataset for 10,000 random replications. This method has been used in [66] and in [48]. We examine the results of samples of 1 up to 300 days.

The clustering approach uses the k-means algorithm. This method groups all hours of the dataset into k different clusters trying to minimize the distance between each observation and the centroids. The k-means algorithm has been used as a scenario reduction approach in [50], [67], [68], and [51]. We use the centroid of each cluster to create representative hours, which are weighted in the objective function in proportion to the size of each cluster. We examine the effect of considering 5 to 2,000 clusters and also consider a variant of this method by forcing the top 10 peak load hours to be included as individual clusters.

As a benchmark, we find the optimal investment decisions with the seven years of hourly data using the probabilistic model with 100 MW of PV (roughly 4% PV penetration on an energy basis). We chose an EUE reliability target of 0.01% of the annual demand.[7] The total installed capacity of the 22 selected conventional generators is 1527 MW with a total cost of \$339.4 million/yr (composed of \$184.4 and \$150.0 million/yr in investment and operational costs, respectively).

We assess the impact of only using a sample of hours (or of using the clusters) by comparing the capacity expansion model decisions and costs with sampling to the capacity expansion model decisions costs with the full dataset. Figure 1 shows the total capacity and cost from the decisions using sampled days divided by the total capacity and cost determined with the full set of seven years of hourly data. Our results suggest that using a sample of less than 10 days is not sufficient to accurately capture the variability of demand and solar resources. As shown in Figure 1, a small sample can bias the investment and operating costs by more than 20% with respect to the results of the full dataset. However, as more days are included, the results found using a sample of days quickly converge to the results with the full seven years of data. A sample of 50 days yields investment decisions and costs that are within +/- 2.5% of the results with the full seven years of data.

We similarly evaluate clustering and constrained clustering with peak hours. The minimum number of clusters required to be within +/- 2.5% of the result from the full sample is more than 2,000 (83 days). Including the top 10 peak demand hours allows 1000 clusters (42 days) to closely replicate the investment decisions from a full seven years of data (within the +/- 2.5% tolerance). This difference in the performance of the clustering algorithm is because the regular k-means method tends to average out the peak hours with some non-peak load hours, which leads to too little investments in generation capacity.[8]

For the remainder of this study we conduct all analyses using the 50 sampled days.

[7] An EUE target of between 0.01% to 0.005% led to a reserve margin of about 9% to 12% of the median annual peak demand.

[8] As a sensitivity analysis we also forced the inclusion of the peak days in the sampling algorithm. However, we find that fifty samples without the peak days provides more accurate results that 50 samples with the peak day. For this particular case, including the peak day in the samples led to investment decisions that over-built the system.

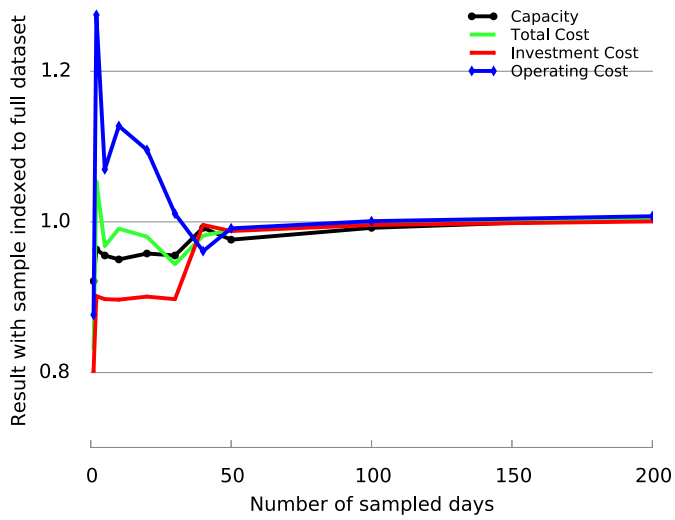

Fig. 1. Capacity expansion decisions and costs of the probabilistic model using sampled days normalized by the results with the full seven-year dataset.

B. Contribution of solar PV towards resource adequacy

The core of any method to assess resource adequacy is to identify periods with high risk of not meeting demand. These periods of high risk, which typically occur during times of high demand, are evaluated endogenously in the probabilistic capacity expansion model and the VDC model. Figure 2 characterizes risk in each hour on a high demand day using three different metrics: the expected energy not served per hour ($U_h = \sum_{s \in S} P_s u_{hs}$) and the loss of load probability (LOLP).[9] The risk metrics for the Demand profile (dashed green line), are based on the generation investments chosen by the probabilistic model without any PV (or wind). As expected, all three metrics show that the periods with high risk of having unmet demand are between noon and 8pm.

We next add 500 MW of PV (roughly 20% PV penetration on an energy basis) and re-solve the probabilistic model. The addition of PV reduces the net demand in the afternoon (solid green line). Since the capacity expansion with and without PV both meet an EUE target of 0.01% of demand, the annual risk level stays the same. The periods of high risk, however, shift from the afternoon (without PV) to the early evening (with PV), when solar resources are no longer producing. It is this shift in high-risk periods to the early evening, depicted through the U_h and LOLP metrics in Figure 2, that causes the deterioration in the capacity value of solar PV at higher penetration levels [55].

Since PV production occurs during periods of high risk, the addition of PV contributes to meeting the resource adequacy constraint. Here we estimate the contribution of PV (or wind) towards resource adequacy by finding the

[9]Note EUE and LOLE are held constant over the year for both the demand and net demand (even though U_h and LOLP appear to have different levels on this peak day). The "risk measure" is a scaled representation of U_h and LOLP, where the scaling factors were chosen to make each metric visible on the same axis.

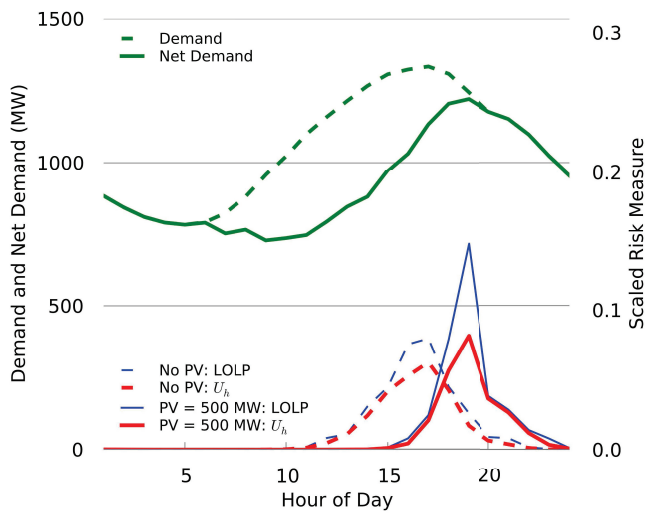

Fig. 2. Periods of high risk with generation investments based on the demand or net demand (with 20% PV).

total installed capacity chosen by the probabilistic capacity expansion model with increasing deployment of PV (or wind). The difference between the installed conventional capacity found for demand alone and the installed capacity with the addition of PV (or wind) is referred to as the capacity contribution.[10]

As expected, we find that the capacity contribution of solar (as a fraction of installed capacity of PV) decreases rapidly as solar penetration increases. For instance, Figure 3 shows that 5% of solar penetration (125 MW of PV) results in a displacement of 50 MW of conventional capacity with respect to the baseline scenario with 0% penetration of solar PV. However, since the high-risk periods shift to the early evening for higher penetration of solar PV, increasing the capacity of solar PV to meet 20% of the annual demand (500 MW of PV) with this resource would only displace 128 MW of conventional generation while maintaining the same reliability level

A simple approach to estimate the capacity value of solar PV is to average the capacity factor of PV generation among the top 10% load hours [11]. This method is justified because the periods of high risk are correlated with periods of peak demand. However, for large penetration levels this method does not account for the shift of the high-risk periods shown in Figure 2. The dashed green line shows the projected capacity value of solar PV approximated by averaging the capacity factor of solar PV based on this method. We find that this capacity-factor based approach can provide a relatively accurate estimation of the capacity contribution of solar towards adequacy for small penetration levels (less than 5%). However, using this approach for higher penetration levels (more than 10%) could significantly overstate the contribution of solar PV. For a 20% penetration the capacity-factor based approximation estimates that the capacity value of solar is nearly 68% (215 MW) more than its true contribution (128 MW).

[10]As a validation experiment we computed the ELCCs for solar and wind for all penetration levels. The capacity contribution measured using either approach, the ELCC or the amount of displaced conventional generation, yield the same results.

On the other hand, we find that the VDC model described in Section II-C can accurately replicate the capacity contribution of solar PV (in terms of magnitude, change with penetration, and difference between PV and wind) found with the probabilistic model. Replicating the behavior of the probabilistic model with the approximation model depends in part on the selection of the reserve margin and δ. The reserve margin is set to 20% and the value of δ is 0.1%. In this case we chose parameter values that produce a good match to the probabilistic model for the no PV case; consequently, these results represent a best-case scenario of the performance of the VDC approximation. In Section IV-E we present results from a sensitivity analysis with respect to different values of the δ parameter.

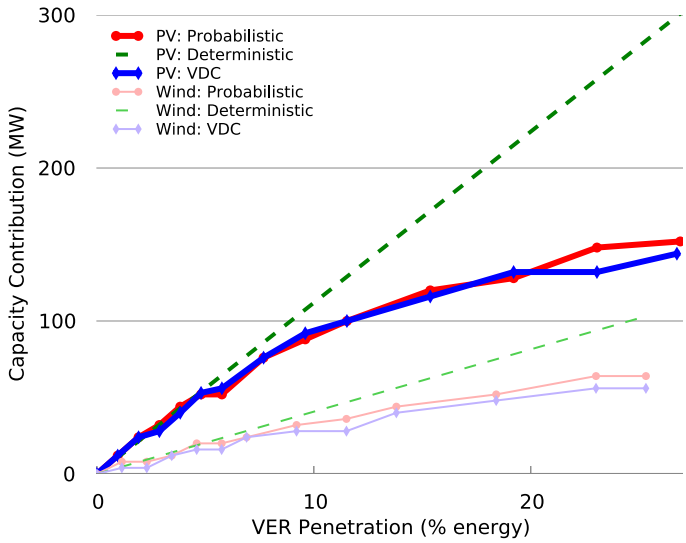

Fig. 3. Capacity contribution of PV or wind (i.e., variable energy resources (VER)) with increasing shares based on the change in investments found using the probabilistic model or the approximation model.

C. Marginal Capacity Contribution

The decision of how much solar PV to add in a capacity expansion model depends on the impact that solar has on the total system cost. In general terms, the investment planning model will add solar capacity until the marginal benefits of this resource equal its marginal cost. One contributor to the marginal benefits of solar is the marginal capacity contribution. To illustrate how the marginal capacity contribution of solar changes with penetration, we fit a 3rd or 4th order polynomial to the capacity contribution line in Figure 3, and then took the derivative of the fit to find the marginal capacity contribution, depicted in Figure 4.

The marginal capacity contribution of PV found by both the probabilistic and the approximation method is above 40% of the nameplate capacity at low penetration levels (less than 2%). However, it falls below 20% for penetration levels above 15%, approximately. In contrast, the marginal capacity contribution of wind is below 20% for low penetration levels and only decreases to 10% for penetration levels above for 15%. This result highlights that taking into account the decreasing capacity value of VERs in generation planning studies is particularly important for solar

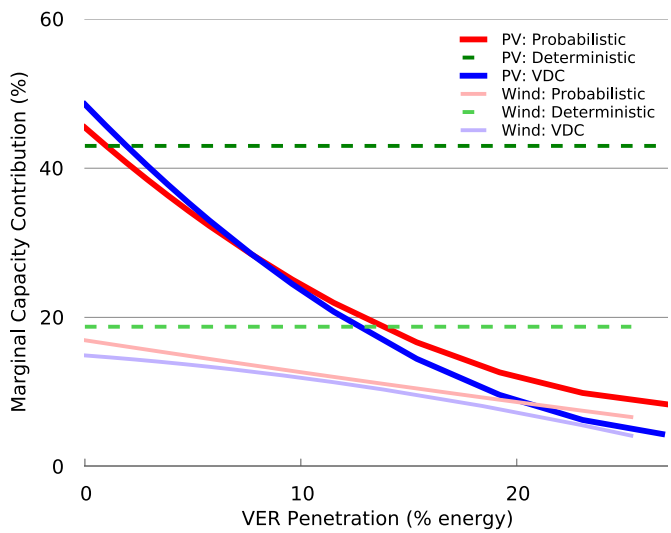

Fig. 4. Estimated marginal capacity contribution of PV and wind.

PV.[11]

We find that the most significant deviation of the results from the probabilistic model and the VDC approximation method occurs with high penetrations of PV (>15% penetration). The VDC approximation method shows that the marginal capacity contribution decreases more rapidly towards 0% at penetrations above 20% than the probabilistic model; the latter continues to show a larger, though still low, contribution. In contrast, the capacity-factor based approximation (dashed green line) yields a constant marginal capacity value that is only accurate for extremely low penetration levels.

The difference in the marginal capacity contribution between the VDC approximation and the probabilistic model for penetrations above 15% is, in part, an artifact of the final results and a consequence of including binary variables for investment decisions. However, for higher penetration levels (i.e., above 50%) we expect to see larger differences between the results of the probabilistic model and the VDC approximation. What occurs is that for high penetration levels of solar PV, the peak net demand will be completely displaced to the early evening, which is when solar PV resources are no longer available. Consequently, at such penetration levels, the peak net demand—and the demand levels in the close neighborhood of it—will be nearly constant with respect to the amount of installed capacity of solar PV. Since in the VDC model installed reserves are defined with respect to the net demand levels in the neighborhood of the peak net demand (for a small $\delta > 0$), this model will predict that the marginal capacity contribution of solar PV for high penetrations will go to zero more rapidly than what we observe in the probabilistic approach. This is, unfortunately, a restriction of the VDC approach that could potentially limit its application to

[11] As pointed out by a referee, the decreasing capacity value is important for regions where the capacity credit at low penetrations is relatively high (e.g. where loads tend to peak on summer days). However, in regions where the capacity credit of PV is low at low penetration levels (e.g. winter night peaking loads), any decline in capacity credit should be less important [69].

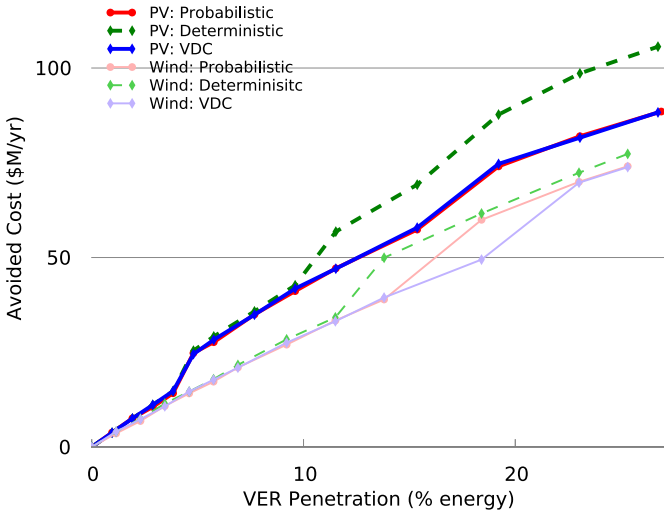

Fig. 5. Avoided total costs with increased PV and wind with both the probabilistic model and the approximation method

moderate penetration levels (i.e., 0%-30% solar PV). However, exploring these differences at such high penetration levels is beyond the scope of this article and we leave as a future research topic.

D. Reduction in Utility Costs

The capacity contribution of solar is important in reducing investments, as is the reduction in the need to dispatch conventional generation. The combination results in the total avoided costs of PV. Here we calculate the total avoided costs as the difference of total system cost in the no PV case and the case with PV, using both the probabilistic model and the approximation method.[12] The same analysis was also done for wind as a comparison.

Figure 5 shows the results for a range of VER penetration. The curves are non smooth due to the lumpiness of generation investment alternatives. Again, the VDC model yields almost identical estimations of avoided costs for solar PV for the whole range of penetration levels analyzed.

Here we measure effect of the inaccuracy of the capacity-factor based approximation (deterministic method) discussed in Sections IV-B and IV-C in economic terms. For penetration levels below 10%, the deterministic method provides an accurate estimate of the avoided costs for both solar PV and wind. However, since at larger penetration levels the deterministic method overstates the capacity value of solar PV (Figure 3), the estimates of the avoided costs computed using this method are biased upwards. For instance, at 20% penetration, both the probabilistic and VDC models estimate that the avoided costs of solar PV are $74 M/year. However, the deterministic approach overstates this value by 19%.

[12]Note that the avoided costs only take into account the economic benefits of adding the resource and not its capital or operating costs.

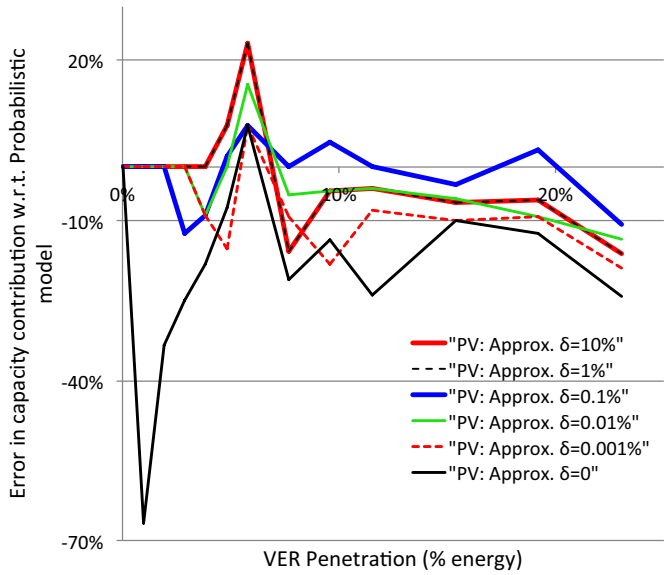

Fig. 6. Error of predicted capacity contribution of Solar PV with respect to probabilistic model

E. Sensitivity analysis with respect to δ

As we mentioned in Section II.C, the choice of the δ parameter can directly affect the ability of the VDC approach to replicate the results from the probabilistic model. Figure 6 shows the error on predicted capacity contribution of solar PV from the VDC model with respect to the probabilistic model for different values of δ.

Choosing a value of δ equal to zero—equivalent to what is used in the SWITCH model—can result in a planning model that underestimates the capacity contribution of solar PV towards resource adequacy by a significant amount. In our case, the maximum error is a predicted capacity contribution that is 66% below the levels of the reference results from the probabilistic model for only 1% penetration of solar power. This occurs because for small penetration levels of solar PV, the magnitude of the peak net demand decreases rapidly as the penetration of solar increases. This directly reduces the contribution of solar PV towards the relaxation on the right hand side of constraints (14), which result in a more stringent (i.e., higher) requirement on reserves from conventional generators (i.e., the left hand side of constraints (14)). The net effect is a reduction in the capacity value of solar PV towards installed reserves, which is reflected as a reduction in the amount of displaced conventional generation needed to meet the installed reserves margin in (14). Although for higher penetration levels the error is smaller in magnitude (10% to 20% of error), we find that choosing a value of δ equal to zero yields the worst approximation to the probabilistic model compared to the rest of the experiments in which we used values of the parameter other than zero.

By increasing the value of δ we are able to reduce the error; the value of δ that yields the best results for our experiments is $\delta = 0.1\%$. The reason the quality of the approximation improves for a larger value of delta is because a (partial) relaxation of constraints (15) allows the VDC model to capture the change of the net demand in a larger neighborhood of the peak-net-demand hour than for $\delta = 0$. There is, however, a trade-off. Selecting

a value of δ that is too large can result in a model where the prime source of error is not the narrowness of the peak-net-demand hours that are ultimately binding in constraints (15) (i.e., the width of a range of hours in the neighborhood of the peak net demand), but the resulting magnitude of the right-hand-side of constraints (14). A large value of δ can result in a model that imposes installed reserves constraints with respect to a reference level (i.e., right hand side of constraints (14)) that is too far below the peak net demand, which is undesirable. In our case, values of δ above 0.1% increased the error for penetration levels above 10%.

Unfortunately, we cannot provide a rigorous method to estimate the value of δ that would result in the best approximation to the probabilistic model. The VDC approach is only an extension of an existing and widely used heuristic-based planning approach that relies on installed reserves margins instead of on strict probabilistic production cost models with standard reliability metrics (i.e., LOLP or EUE). Despite this limitation, our numerical results suggest that using values of delta in the neighborhood of 0.1% could significantly improve the ability of existing deterministic-based models (e.g., SWTICH) to endogenously capture the deterioration in the capacity value of solar PV with increasing penetrations of the resource.

F. Computational Performance

All models were implemented in the Coopr open-source Python library [70] and run on a 48-core workstation with 512GB of RAM. All optimization problems were solved using the CPLEX 12.6 solver. Solution times for the probabilistic method range from 2 hrs. for the full 7-year dataset to an average of 185 sec. for a 50-day sample. Table III shows solution times for the deterministic, VDC, and probabilistic models for a different levels of installed PV capacity. We find that expanding the deterministic model to account for the additional constraints associated with the VDC model only increases solution times by an average of 4 sec. (16%) in average. In turn, the full probabilistic approach is nearly 6 times slower than the VDC method.

TABLE III
SOLUTION TIMES

PV	Solution Time [s]		
Capacity [MW]	Deterministic	VDC	Probabilistic
25	32.2	47.3	84.2
50	37.4	39	93.5
75	39.7	36.2	170.5
100	38.2	35.8	151.7
125	21.3	23.8	94.9
150	19.9	26.9	229.0
200	21.4	28.4	205.5
250	22.1	26.4	231.1
300	18.1	25.1	222.0
400	20.7	22.1	285.5
500	17.9	21.3	212.2
600	17.5	22.1	244.0

Although these improvements might not seem significant, we want to highlight that the test case we employed in our paper to perform all the experiments (IEEE RTS) is significantly smaller than a real-world system such as CAISO, MISO, ERCOT, or PJM. Note that the size of the probabilistic problem grows exponentially with the number of generators since it considers the full distribution of outage scenarios for the whole system (i.e., the number of outage scenarios per hour equals 2^N, where N is the number of generator units in the system). In contrast, the deterministic and VDC models do not consider outage scenarios and, therefore, they grow linearly as a function of the number of generators. Hence, we believe that the solution time savings from using the VDC model instead of the probabilistic one will be two orders of magnitude, at a minimum, for large-scale systems.

There are also modeling benefits related to using the VDC approach instead of the probabilistic model. Some of these include a) the possibility of modeling environmental constraints such as renewable targets and emissions limits, b) accounting for chronological constraints such as ramping limits and storage balance equations, and c) modeling of transmission constraints. These are important features that are often included in high-level energy planning models for policy analysis, such as ReEDS [59], SWITCH [60], and IPM [46], but that we did not consider in this article. Accounting for a) and storage in b) within the probabilistic model is possible, but doing so would require non-trivial modifications to the decomposition-based solution method proposed by Bloom [20], which is the industry standard for solving probabilistic production cost models. Unfortunately, adding ramping limits and/or transmission constraints to the probabilistic model would result in a formulation that would not be solvable using Bloom's method and that, in all likelihood, would not be solvable using a commercial off-the-shelf solver either. In turn, a), b), and c) are all features that could be easily incorporated into the VDC model without adding much more complexity to it; however, their implementation and a study of their effect on the quality of the VDC approximation is beyond the scope of this article.

V. Conclusions

In this article we show that the contribution of PV (and wind) to maintaining resource adequacy can be represented in capacity expansion models endogenously. Our main contributions are a threefold. First, we perform the first analysis of the capacity contribution of solar PV (and wind) using a probabilistic capacity expansion model that considers the full space of generator outages and that can be solved to optimality. Second, we compare the accuracy of existing deterministic planning methods to predict the economic value of solar PV (and wind). Third, we propose a variant of the deterministic reserve margin planning approach that can reasonably replicate the behavior of the more detailed probabilistic model over a range of penetrations of solar PV (and wind).

We find that daily or hourly sampling techniques can be used to reduce the computational complexity in capacity expansion models. Our results suggest that only a small fraction of hourly data (50 days) is needed to replicate the results of the probabilistic model using a seven-year dataset (2,557 days), but which is more than what it is often used in capacity expansion models.

With the probabilistic model we confirm that the capacity value of solar PV decreases rapidly as penetration increases. The contribution of PV to resource adequacy is high (>40% of the nameplate capacity) at low penetration

levels, but the marginal contribution declines with increasing penetration. The decline was due in part to the periods of high risk shifting from the late afternoon to early evening. In contrast, a capacity-factor based approach (deterministic model) significantly overestimates the contribution of solar PV towards resource adequacy. For a 20% penetration the capacity-factor based approximation estimates that the capacity value of solar is nearly 68% (215 MW) more than its true contribution (128 MW). This discrepancy is directly reflected in the estimated avoided cost for the same penetration level. The deterministic model overestimates the avoided cost of solar by 19% with respect to what is computed using the probabilistic model.

Due to the importance of contributions to resource adequacy to the overall economic value of PV, it is important that capacity expansion models carefully represent this change in contribution with increasing penetration. The VDC model presented here is one promising approach that does not significantly increase the computational burden. However, for small penetration levels the capacity-factor based method provides a reasonably accurate estimate of the capacity contribution and avoided cost of PV. Thus, in the context of identifying cost-effective portfolios of generation, the VDC model (for a range of VER penetrations) or deterministic model (for low penetrations) could be help planners identify high quality investments strategies. Though it is important to recognize that they do not replace detailed probabilistic production cost simulations.

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