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A Simple and Fast Algorithm for Estimating the Capacity Credit of Solar and Storage

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Abstract

Energy storage is a leading option to enhance the resource adequacy contribution of solar energy. Detailed analysis of the capacity credit of solar energy and energy storage is limited in part due to the data intensive and computationally complex nature of probabilistic resource adequacy assessments. This paper presents a simple algorithm for calculating the capacity credit of energy-limited resources that, due to the low computational and data needs, is well suited to exploratory analysis. Validation against benchmarks based on probabilistic techniques shows that it can yield similar insights. The method is used to evaluate the impact of different solar and storage configurations, particularly with respect to the strategy for coupling storage and solar photovoltaic

systems. Application of the method to a case study of utilities in Florida, where solar is rapidly growing and demand peaks in the winter and summer, demonstrates that it can improve on rules of thumb used in practice by some utilities. If storage is required to charge only from solar, periods of high demand driven by cold weather events accompanied by lower solar production can result in a capacity credit of solar and storage that is less than the capacity credit of storage alone.

Key words: capacity credit; resource adequacy; solar; energy storage; utility planning

1. Introduction

Worldwide, renewable energy is expected to grow by 50% between 2019 and 2024 with solar photovoltaics (PV) making up 60% of all renewables [1]. One factor contributing to the attractiveness of solar PV is its relatively high economic value in regions where solar production is aligned with periods of peak electricity demand [2]. Increasing the share of generation from solar PV, however, can shift timing of peaks in net demand (demand less solar PV generation) and displace generation with lower variable costs [3]. These changes contribute to a declining economic value of solar with higher penetration [4]. Energy storage stands out as one of the more effective strategies to mitigate the decline in economic value of solar PV. In a scenario with 30% of annual energy met by solar PV, Mills and Wiser [5] find that the marginal economic value of solar PV increases by 80% when low-cost storage is deployed in the power system compared to a reference case without storage. Energy storage can also be deployed at the same physical location as solar in a hybrid solar + storage facility. In the U.S., storage is eligible for the Federal Investment Tax Credit (ITC), equivalent to a 30% reduction in capital costs, when storage can be shown to charge from solar rather than from the grid. Commercial activity related to hybrid solar + storage plants is growing rapidly in the U.S., particularly in California where recent wholesale electricity market prices indicate the potential additional revenue from adding storage exceeds the additional cost (accounting for the ITC) [6].

One of the sources of economic value of solar + storage plants is its contribution toward meeting resource adequacy requirements. Adequacy is an aspect of overall power system reliability that “relates to the existence of sufficient facilities within the system to satisfy the consumer load demand or system operational constraints” [7]. In this paper the contribution of a resource toward adequacy is called the capacity credit. Estimates of a resource’s capacity credit are often based on a probabilistic assessment that considers its reduction to the risk of a loss of load when available supply is less than demand. A prevailing method for estimating the capacity credit with a probabilistic assessment is called the effective load carrying capability (ELCC). The drivers of the capacity credit of stand-alone solar PV using probabilistic assessments are well established [8]. Many regulators, utilities, and regional planners account for the capacity credit of stand-alone solar PV in economic valuation studies [9]. Of particular importance, the capacity credit of solar declines with increasing penetration of solar PV as the timing of periods with the highest risk of insufficient generation can shift from the peak demand in the afternoon to peak net demand periods in the early evening when the sun sets [10]. Munoz and Mills show the importance of accounting for the decline in capacity credit of solar PV in capacity expansion modeling [11].

In contrast, the capacity credit of solar + storage resources is not yet well understood. The objective of this paper is to develop methods for exploring the drivers of the capacity credit of solar + storage. In practice, rules of thumb are used to determine the capacity credit of a combined resource. One approach is to calculate the capacity credit of solar + storage as the sum of the capacity credit of the independent components (e.g., the capacity credit of stand-alone solar plus the capacity credit of stand-alone storage) limited by the capacity of any shared equipment such as an inverter or point of interconnection limit. This rule of thumb is used for evaluating resource adequacy contribution of solar + storage in California [12] and for evaluating candidate resources for procurement in Colorado [13].

More generally, methods for calculating the capacity credit of energy-limited resources, including energy storage, are nascent. Sioshansi et al. [14] develop probabilistic methods to quantify the capacity credit of storage accounting for the storage level at the time of an outage and, through dynamic programming techniques, potential subsequent outages in later hours. Previous estimates of storage's capacity credit with probabilistic techniques from Tuohy et al. [15] do not account for subsequent outages, potentially overstating the contribution of storage. Both Sioshansi et al. [14] and Tuohy et al. [15] calculate the starting storage level in each hour assuming it is dispatched to maximize revenue from energy arbitrage, rather than to maximize the capacity credit. Alternatively, Parks [16] modifies the traditional probabilistic techniques to maximize the capacity credit of energy-limited resources by discharging the energy-limited resources in periods of highest risk of a loss of load. Hall et al. [17] use a similar technique to find the capacity credit of storage for the New York Independent System Operator. Byers and Botterud [18] use probabilistic

methods to calculate the capacity credit of energy storage based on Monte Carlo simulations of system-wide chronological unit commitment and economic dispatch. Additional variations on probabilistic techniques for finding the capacity credit of energy-limited resources include a two-stage optimization approach by Zhou et al. [19] and an approach by Nolan et al. [20] to calculate the capacity credit of a given demand response time series based on the assumption that demand response is dispatched to reduce peak demand.

A common challenge with probabilistic techniques is the large computational burden and detailed nature of the data required to conduct this analysis. This makes it more difficult to quickly explore the way capacity credit varies depending on technology configurations and characteristics of demand. Several simple alternatives to probabilistic techniques have been used in the literature. Denholm et al. [21] estimate the capacity credit of storage as the difference between the maximum demand and the maximum demand net of the storage dispatch. Storage discharge is chosen to maintain the maximum net demand at or below a target level and it can charge any time that does not increase the maximum net demand. Richardson and Harvey [22] use storage to evenly allocate solar PV production across a day to meet a constant fraction of the demand above the minimum demand. They then calculate the capacity credit of the combined solar + storage facility using the Garver approximation to the effective load carrying capability [23]. Fattori et al. [24] dispatch storage to smooth the net demand profile based on a moving average window of different durations. The capacity credit is then based on the difference between the peak demand

and peak demand net of solar + storage. None of these simple alternatives are directly validated against the more detailed probabilistic techniques.

This paper presents a simple algorithm for calculating the capacity credit of energy-limited resources that, due to the low computational and data needs, is well suited to exploratory analysis. Importantly, validation against benchmarks based on probabilistic techniques shows that estimates based on the method can yield similar insights. The simple nature of the capacity credit calculations is used to evaluate the impact of a wide variety of different solar + storage configurations, particularly with respect to the strategy for coupling storage and solar PV. The case study focuses on Florida where solar is rapidly growing and demand peaks in the winter and summer.

2. Methods and Data

The foundation of this capacity credit calculation is the load duration curve (LDC) method employed in two capacity expansion models developed by the National Renewable Energy Laboratory (NREL) called the Regional Energy Deployment System (ReEDS) [19] and Resource Planning Model (RPM) [25]. With the LDC method, the capacity credit is calculated as the reduction in the average highest peak net load hours relative to the average highest peak load hours. The calculation method can be visualized as the difference between an LDC, which sorts the load from the highest to the lowest over a specified period, such as a year, and a net LDC during the peak hours (Figure 1). Here the peak hours are defined as the top 100 hours of the year (the top 1.1% of hours). The net LDC is created by first reducing the hourly load by the corresponding generation from the

resource in the same hour and then sorting the resulting net load from highest to lowest. Because the load and net load duration curves are sorted independently, the gap between the load and net load duration curves represents the decrease in the highest net load hours, irrespective of when they occur. The LDC method can therefore capture any effects where deployment of a resource leads to a shift in the time of day or season in which the net load peak hours occur.

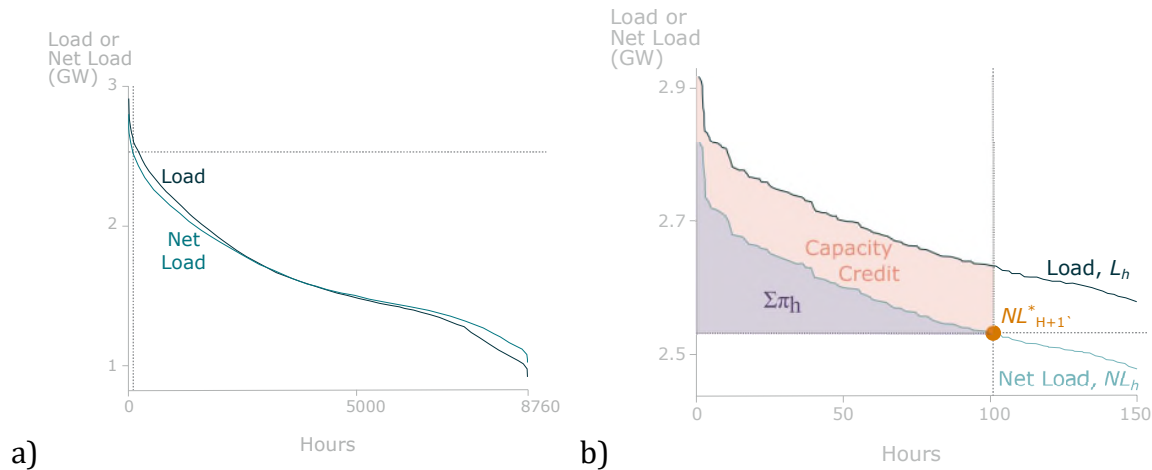


Figure 1. Illustration of load and net load duration curves for all hours of a year (a) and focusing on just the peak hours of a year (b).

In the case of energy-limited resources, the LDC method defines how to calculate the capacity credit for a given dispatch profile, but it does not specify how to dispatch resources to maximize its capacity credit. Section 2.1 presents an algorithm for finding the dispatch of energy-limited resources, which is central to calculating the capacity credit of storage using the LDC method as summarized in Figure 2. Sections 2.2 and 2.3 describe an approach to validate the capacity credit calculated with the LDC method against two benchmarks based on probabilistic techniques.

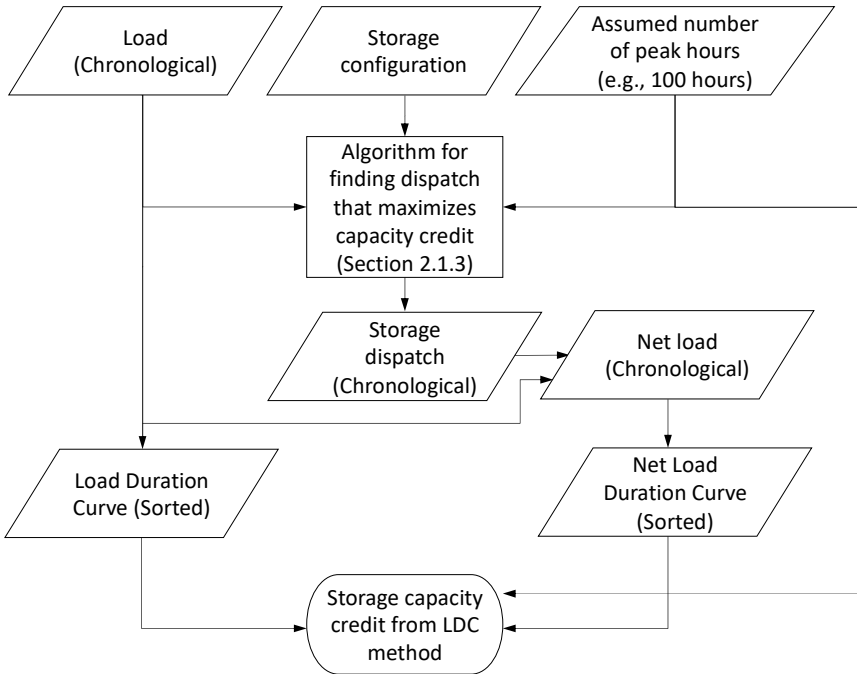


Figure 2. Illustration of the method for estimating the capacity credit of storage.

2.1 Dispatch Algorithm

The dispatch algorithm is a linear programming model whose solution maximizes the capacity credit of storage, where the capacity credit is defined based on the LDC method. In the case of storage, the net LDC is created by both reducing demand by the energy generation from discharging storage and increasing demand by the energy required for charging storage.

The approach leverages insights from the literature on optimizing the conditional value at risk (CVaR) [26] and the fact that maximizing the capacity credit of a resource, based on the LDC method, is equivalent to minimizing the area under the net LDC in the peak net load hours. Because the resulting optimization model is linear, it can be constructed and solved

within 20 seconds on a computer with a 2 GHz processor using an open source solver (e.g., GLPK [27] with the Pyomo package for Python [28], [29]).

The basics of the CVaR optimization formulation and its adaptation to capacity credit maximization are presented before the specific application of finding the dispatch of energy storage.

2.1.1 Conditional Value at Risk Optimization Formulation

In mathematical finance theory, one of the most widely used coherent measures of risk is the so-called CVaR index [30]. The VaR (value at risk) calculates the losses of an investment portfolio with a specified probability. For example, the losses of an investment will have a 5% probability of being higher than the VaR at 95%. The conditional value at risk (CVaR) at 95% represents the average losses in those 5%-probability worst cases. Thus, it is directly proportional to the area of the density function for those 5% worst cases.

The CVaR optimization formulation minimizes the risk associated with buying a portfolio of assets by minimizing the CVaR at a certain percentile, according to different returns associated with several scenarios.

Given a portfolio of n assets, let X_i be the per-unit amount of each one:

$$\sum_{i=1}^n X_i = 1$$

(1)

Let $s = 1, \dots, S$ be the different scenarios considered for the evolution of the price of the different assets. For each considered scenario s , the losses per stock can be calculated as the product of the per-unit amount times the loss r_{is} for each asset in each scenario. Hence, the total losses for each scenario can be calculated as:

$$L_s = \sum_{i=1}^S X_i \cdot r_{is} \quad (2)$$

Having the density function for the total losses, and given a percentile, the VaR is defined as the value of the density function at that specific percentile (α). Typically, a 95% percentile is used (VaR_{95%}). As mentioned, the CVaR is defined as the mean of losses in the 5% (or whatever VaR) tail of the distribution.

The CVaR minimization for a percentile α can be expressed in equation (3).

$$CVaR_\alpha = \min_{VaR, X_i, L_s} \left\{ VaR_\alpha + \frac{1}{1-\alpha} \mathbb{E}[\max(L_s - VaR_\alpha, 0)] \right\} \quad (3)$$

Rockafellar and Uryasev [30] prove that this CVaR minimization can be solved by using the linear optimization problem described by equations (4–7).

Objective Function:

$$\min_{VaR, X_i, u_s} \left\{ VaR_\alpha - \frac{1}{(1-\alpha) \cdot S} \cdot \sum_{s=1}^S u_s \right\} \quad (4)$$

Subject to:

$$u_s \geq \sum_{i=1}^n X_i \cdot r_{is} - VaR_{\alpha} \quad s = 1, \dots, S \quad (5)$$

$$\sum_{i=1}^n X_i = 1 \quad (6)$$

$$u_s \geq 0 ; X_i \geq 0 \quad (7)$$

This methodology can be applied in other contexts where areas below some curves must be minimized or maximized. Particularly, the CVaR model can be adapted to maximize the capacity credit of a resource defined with the LDC method, because the final objective is to minimize the area below the net load curve during peak hours.

2.1.2 Application of Conditional Value at Risk Optimization to Capacity Credit Maximization

The application of the CVaR optimization to the maximization of the capacity credit for storage facilities can be understood through an analogy between the different problems to be solved.

On the one hand, CVaR minimization can be expressed through equation (3). On the other hand, trying to maximize the capacity credit is equivalent to minimizing the net load, NL_h ,

for the H peak hours. Minimizing the net load can be carried out through a minimization of the area below the net load-duration curve for the first H hours. The primary contribution of this paper is to connect the goal of maximizing the capacity credit of a resource, based on the LDC method, to its equivalent formulation in equation (8) which minimizes the area under the net LDC in the peak net load hours.

$$Area_H = \min_{NL_{H+1}, X, NL_h} \left\{ NL_{H+1}^* + \frac{1}{H/8760} \mathbb{E}[\max(NL_h - NL_{H+1}^*, 0)] \right\} \quad (8)$$

Where, as shown in Figure 1b, NL_{H+1}^* represents the net load level at the peak hour $H+1$, NL_h the net load for hour h , and X the storage dispatch decisions (subject to all the operational and technical constraints of the storage system, such as chronology, maximum level of storage, and maximum output).

An analogy between both problems shows how an equivalent linear problem can be used to solve the capacity credit maximization. The losses for each stock are analogous to the net load of the system after the storage dispatch for every hour has been determined. Scenarios in CVaR minimization are substituted by hours in the capacity credit maximization. Finally, the confidence level α will correspond to the ratio of non-peak hours, that is $(8760 - H)/8760$. The parallelism between both formulations is summarized in Table 1. The other major contribution of this paper is to leverage the insight from Rockafellar and Uryasev's solution to the CVaR minimization problem [30] to convert equation (8) into an equivalent linear problem, as described next.

Table 1. Analogy between Conditional Value at Risk and capacity credit formulation

Conditional Value at Risk (CVaR) formulation	Capacity credit formulation
Objective Function: Min CVaR	Objective Function: Max capacity credit = Min Average Net Load for H peak hours
VaR_α	Net Load for hour H+1 in the net load duration curve NL^*_{H+1}
Confidence level α	Ratio of non-peak hours $(8760-H)/8760$
Scenarios $s = 1, \dots, S$	Hours $h = 1, \dots, 8760$
Losses (L_s)	Net load (NL_h)
Stock portfolio decisions	Storage operation decisions

2.1.3 Detailed Formulation for Capacity Credit Maximization of Storage

Applying the capacity credit formulation to storage requires fully modeling the storage dispatch decisions. This formulation characterizes a storage system by its nameplate capacity (MW), its energy capacity (MWh), and its roundtrip efficiency. It also assumes the storage system charges and discharges at rates up to its nameplate capacity. The storage duration (in hours) is therefore the ratio of the energy capacity to the nameplate capacity. The analysis uses hourly time steps—no shorter time constraints or ramping limits have been considered. The model also assumes perfect foresight over the whole analysis period.

Because the model searches for an optimal storage dispatch profile, the hourly system demand net of storage generation (the net load) is also a decision variable obtained from the model. The decision variable of the level of the net load just outside of the peak net load

hours, NL^*_{H+1} , is especially significant, as it defines the area of the net LDC that when minimized leads to the storage dispatch with the maximum capacity credit.

The calculation details are as follows:

1. Indexes and Parameters

h Index for hours in the analysis, typically 8,760 hours for 1 year

L_h System load in hour h (MW)

Bp_{Max} Nameplate capacity of storage (MW)

Bl_{Max} Maximum level of storage (MWh)

η Roundtrip efficiency of storage (%)

H Number of peak hours

2. Variables

Bo_h Discharge power from storage to the grid (MW)

Bi_h Charging power from the grid to storage (MW)

Bl_h Storage level (MWh)

NL_h System net load in hour h (MW)

NL^*_{H+1} Net load in hour $H+1$ (a level chosen by the model)

π_h Continuous auxiliary variable equal to the maximum of $[NL_h - NL^*_{H+1}]$ and 0

3. Objective Function

$$\min \left\{ NL^*_{H+1} + \frac{1}{H} * \sum_{h=1}^{8760} \pi_h \right\}$$

(9)

4. Operational Constraints

Load and Net Load

$$NL_h = L_h + Bi_h - Bo_h \quad (10)$$

Identify Peak Hours

$$\pi_h \geq NL_h - NL_{H+1}^* \quad (11)$$

Ignore Net Load in Non-peak Hours

$$\pi_h \geq 0 \quad (12)$$

Storage Energy Balance

$$Bl_h = Bl_{h-1} + \eta \cdot Bi_h - Bo_h \quad (13)$$

Maximum Storage Level

$$Bl_h \leq Bl_{Max} \quad (14)$$

Maximum Storage Discharge

$$0 \leq Bo_h \leq Bp_{Max} \quad (15)$$

Maximum Storage Charge

$$0 \leq Bi_h \leq Bp_{Max} \quad (16)$$

The objective function, equation (9), minimizes the area under the net LDC curve in the peak net load hours, as illustrated in Figure 1b. It is analogous to equation (4) in the CVaR minimization problem. The constraints that identify which hours are peak net load hours,

equations (11) and (12), are analogous to equations (5) and (7), respectively, in the CVaR minimization problem. The remaining equations define the net load and storage constraints.

2.2 Validation 1: Florida Utility Benchmark

In the first validation, the dispatch of storage is found by solving equations (9–16). That storage dispatch is then used to compare the capacity credit based on the LDC method to the ELCC of storage using the probabilistic approach outlined by Keane et al. [31], similar to the way Nolan et al. use the time series of demand response to calculate its ELCC [20].¹ The probabilistic benchmark accounts for the probability that random forced outages at power plants will lead to insufficient generation to meet demand in any hour, as quantified by the loss of load probability (LOLP). Overall reliability is then measured by the loss of load expectation (LOLE), which accumulates the LOLP over all hours. The ELCC represents the amount that the demand can be increased after a resource is added to the generation mix while maintaining the same level of overall reliability.

The capacity credit from the LDC method is compared to the ELCC using demand and generation data from three municipal utilities in Florida: JEA, City of Tallahassee, and the

¹ The level of reliability based on the generation and demand can change from year to year. Similar to the approach used by Madaeni et al [32], load levels are scaled so that the LOLPs of the base system in each year sum to 2.4 in order to have a consistent starting point for determining the reliability contribution of solar and storage.

Florida Municipal Power Pool (FMPP²). Hourly load data for the three utilities is from ABB Velocity Suite (based on Federal Energy Regulatory Commission Form 714) for 2006–2016. Peak demand for JEA, City of Tallahassee, and FMPP was 3.3GW, 0.63 GW, and 3.7 GW, respectively. Nameplate capacity and forced outage rate for generators associated with each utility are also from ABB Velocity Suite, augmented with 10-year site plans filed with the Florida Public Service Commission [33]. The largest single generator for JEA, City of Tallahassee, and FMPP was 600 MW, 350 MW, and 450 MW, respectively. For the City of Tallahassee, a small utility with a relatively large generator and a limited number of small generators, also includes 200 MW of firm capacity based on transmission capacity between the City of Tallahassee and resources in Georgia. This transmission capacity is not tied to any one generator, but provides the City of Tallahassee with access to a wide variety of resources at times when its own units experience forced outages.

Finally, the capacity credit of stand-alone solar PV based on the LDC method is compared to the ELCC for the same utilities. Solar PV generation profiles for 2006-2016 are based on the default assumptions in NREL's PVWatts model [34], with historical weather data sourced from the National Solar Radiation Database [35] for particular hypothetical PV sites located near each utility.

² FMPP member utilities include the Orlando Utilities Commission, Lakeland Electric, and the Florida Municipal Power Agency. FMPP operates the combined resources of the utilities as if they were one utility.

Throughout the analysis, the roundtrip efficiency of storage (η) is assumed to be 85%, similar to the roundtrip efficiency of a lithium-ion battery [36].

2.3 Validation 2: Western United States Utility Benchmark

In the second validation, the ELCC of 4-hour duration storage calculated by a utility in the western U.S. using method described by Parks [16] is compared to the capacity credit with the LDC method of 4-hour storage dispatched using equations (9-16). The capacity credit from the ELCC and LDC methods both use the same demand and variable renewable energy data from the western U.S. utility. The capacity credit of storage is considered under two different scenarios: one with near-term solar penetration levels (“Low Solar”) and one with solar penetration levels that reflect expected expansion in solar by 2030 (“High Solar”). The utility has a peak demand of more than 7GW. The ELCC is based on the utility having a target LOLE of 2.4 hours/year.

The primary difference between this validation and Validation 1 is that here the utility independently develops the storage dispatch profile for the ELCC calculation. In contrast, in Validation 1 the storage dispatch profile from solving equations (9–16) is used to calculate the capacity credit both with the LDC method and with the ELCC method. In conjunction with the results from the first validation, the second validation also illustrates the applicability of the method to multiple regions.

2.4 Case Study

The case study employs the dispatch algorithm in Section 2.1 to an evaluation of the capacity credit of different possible configurations of solar + storage for two Florida utilities, FMPP and JEA. The hourly demand and solar PV generation data described in Section 2.2, focusing only on data from representing 2012, are used in the case study. Though there are many factors to consider when sizing storage and solar and deciding on the configuration, the focus of this paper is solely on the implications for the capacity credit of solar + storage.

The factors that developers can adjust when designing a solar + storage system include the number of hours of storage, the storage power capacity relative to the PV module capacity, the ratio of the inverter capacity to the PV module capacity, whether the solar and storage are independent (alternating current [AC] coupled) or share an inverter (direct current [DC] coupled), and whether the storage can charge from the grid or solar (loosely coupled) or whether it can only charge from solar (tightly coupled).³ One reason storage might be restricted to only charge with solar power relates to tax credit policy. Currently, storage can qualify for the U.S. federal Investment Tax Credit (ITC) that is available for solar plants if the storage charges from solar at least 75% of the time (with the maximum credit available if it charges from solar 100% of the time). The implications of the different configurations on solar + storage capacity credit are shown by comparing results for the extreme case in which storage is only charged from solar or it can be charged from either

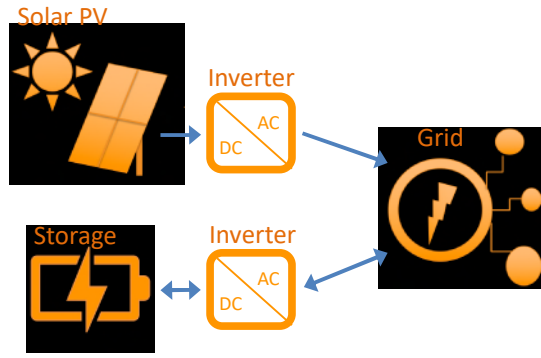
³ This follows the naming convention for this configuration as described by Denholm et al.

[37]

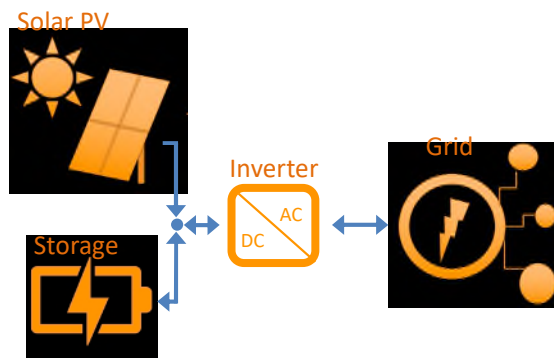
the grid or solar (Table 2). In all coupled cases, the ratio of the inverter capacity to the PV module capacity is kept constant, rather than changing the inverter size as storage is added. The different configurations are illustrated in Figure 3.

Table 2. Definition of solar + storage configurations

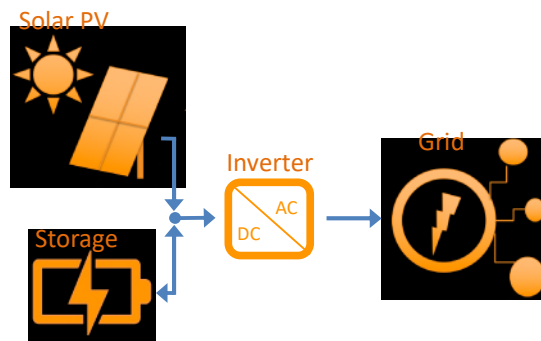
Configuration	Description	Share Equipment?	Source of Electricity for Storage
Independent	PV and storage do not share equipment, and storage is charged from the grid.	No	Grid
Loosely Coupled	PV and storage both connect on the DC side of shared inverters, but storage can charge from storage or the grid.	Shared inverter	Grid or PV
Tightly Coupled	PV and storage connect on the DC side of shared inverters, and storage can only charge from PV.	Shared inverter	Only PV



(a)



(b)



(c)

Figure 3. Illustration of solar + storage configurations (a) independent, (b) loosely coupled, (c) tightly coupled

3. Results and discussion

Results begin with the validation of the method described in Section 2.1 based on two different benchmarks. The method is then used to explore the capacity credit of different solar + storage configurations for two of the Florida utilities.

3.1 Validation 1: Florida Utility Benchmark

The capacity credit estimated with the LDC method is compared to the ELCC calculated with a probabilistic method for different storage durations using data from three Florida municipal utilities in Figure 4. As point of comparison, the capacity credit for stand-alone PV is also shown using both methods. The sensitivity of the capacity credit to different weather patterns is highlighted by the range of values depending on which year of data was used between 2006-2016. The capacity credit is also calculated using all 11 years of data at one time. In this case, the LDC method maximizes the capacity credit over the peak 1100 hours (i.e., the peak hours continue to be defined as the top 1.1% of all hours).

Irrespective of the calculation method, these results show that even though storage is fully dispatchable, its capacity credit is highly dependent on the duration of storage. With too few hours of energy, storage cannot continuously reduce the peak net load hours on days with high, broad peaks. On these days, storage is more likely to be depleted when reducing peak load, leaving it unavailable for discharge during other peak hours. Because storage's capacity credit depends on load shape, it can vary from year to year. Storage with a given duration is more likely to have a higher capacity credit in years with narrower peaks, while achieving a high capacity credit in years with broader peaks requires longer-duration

storage. These findings are in line with previous estimates based on detailed probabilistic methods (e.g., [14]).

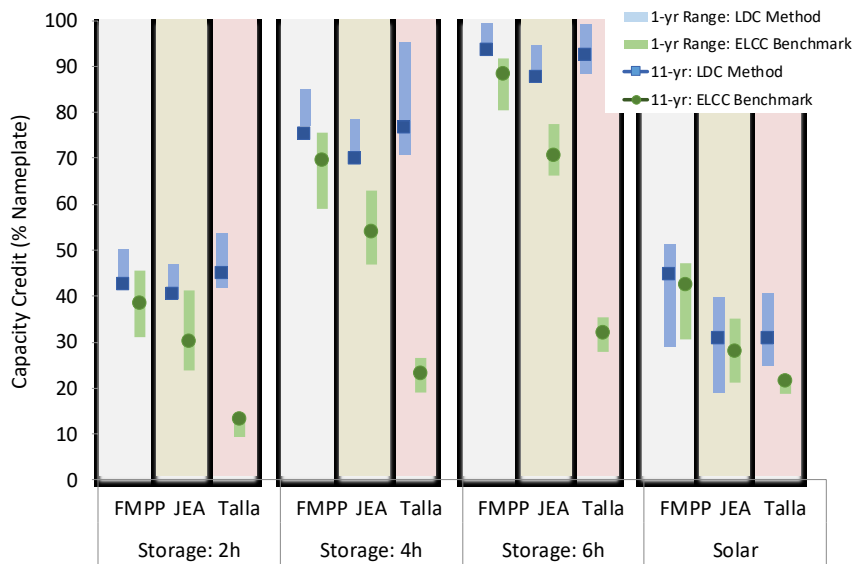


Figure 4. Comparison of the capacity credit estimated with the load duration curve (LDC) method to the effective load carrying capability (ELCC) calculated with a probabilistic method for the Florida utilities.

The 20-50% capacity credits of solar are within the range of solar capacity credits, at low penetrations, reported in other studies or assumed in utility planning studies, though at the lower end [38], [39]. The solar capacity credit is somewhat lower than the 54% capacity credit assigned to solar by a major investor-owned utility, Florida Power & Light (FPL), in its evaluation of the cost-effectiveness of proposed solar plants. FPL estimates the capacity credit based on the expected solar generation during the typical peak demand periods of 4-5pm in August [40].

For the two larger utilities with peak demand over 3 GW (JEA and FMPP), the capacity credit with LDC method is directionally consistent and quantitatively similar to the ELCC

benchmark for both storage and stand-alone solar. For these two utilities, the main difference is that the LDC method tends to overestimate the capacity credit of storage and stand-alone solar, particularly for longer storage durations. Even for the small utility with a peak demand of less than 1 GW (City of Tallahassee), the solar capacity credit with the LDC method is somewhat similar to, though slightly higher than, the ELCC.

On the other hand, for the small utility (City of Tallahassee), the capacity credit of storage estimated with the LDC method is much greater than the ELCC. This starkly different result stems from the small number of conventional generating stations operated by Tallahassee, with some relatively large compared to the load, which leads to a widely distributed risk of outages (or a widely distributed LOLP). Whereas the risk is concentrated in less than about 0.5% of the hours for JEA and FMPP, Tallahassee's risk is distributed over about 17% of the year, Figure 5.⁴ As a result, short-duration storage makes a much smaller contribution to increasing the overall system reliability for the City of Tallahassee compared to the contribution of storage in JEA and FMPP.

⁴ The concentration of the risk of outages is measured as the percentage of hours in which the LOLP is greater than 5% of the maximum LOLP. A smaller percentage of hours in which the LOLP is greater than 5% of the maximum indicates that the risk of outage is more concentrated in peak hours.

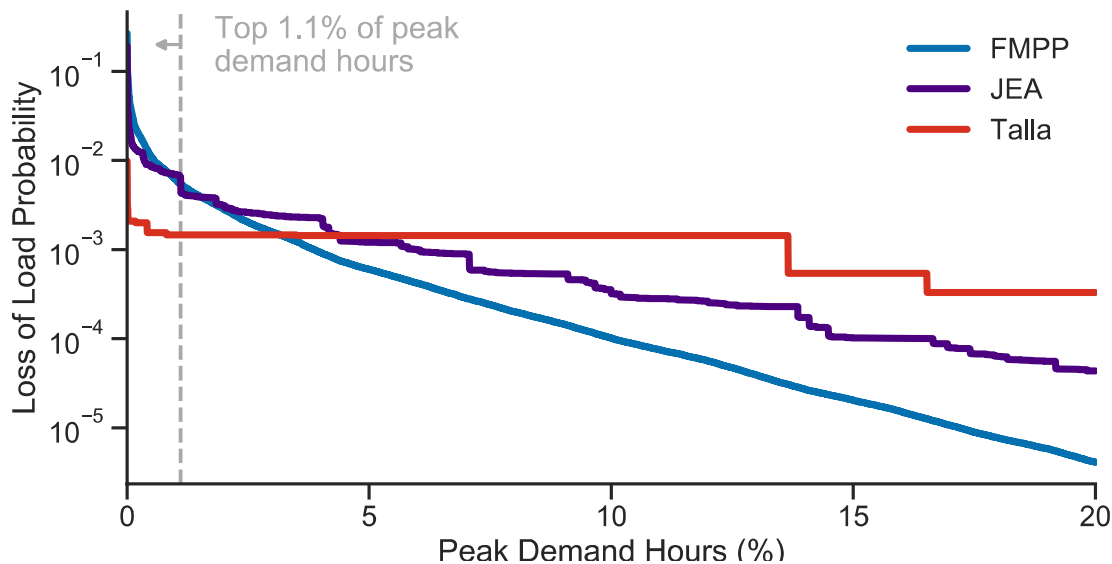


Figure 5. Comparison of the concentration of risk of outages in peak hours between three Florida utilities

Though the deviation between the capacity credit estimated with the LDC method and the ELCC for the City of Tallahassee is important to understand, this situation is expected to be rare. Few utilities are as small as the City of Tallahassee, and even among small utilities it is unusual to find individual generators that constitute such a large fraction of the total capacity. More generally, since each utility is modeled in isolation, several factors that could be important in determining the true risk profile for utilities are not addressed. These include the potential to access generation over other transmission lines and to leverage shared reserves for short-term events. Probabilistic methods that can account for transmission capacity to neighboring utilities exist [41], though they are not considered in this validation.

3.2 Validation 2: Western United States Utility Benchmark

Here the capacity credit of storage, found using the algorithm described in Section 2.1, is compared to the ELCC calculated from a detailed probabilistic loss of load probability model. In this validation the dispatch of the storage was also done independently. Figure 6 compares the marginal capacity credit of additional 4-hour duration storage as increasing amounts of storage are added to the system.

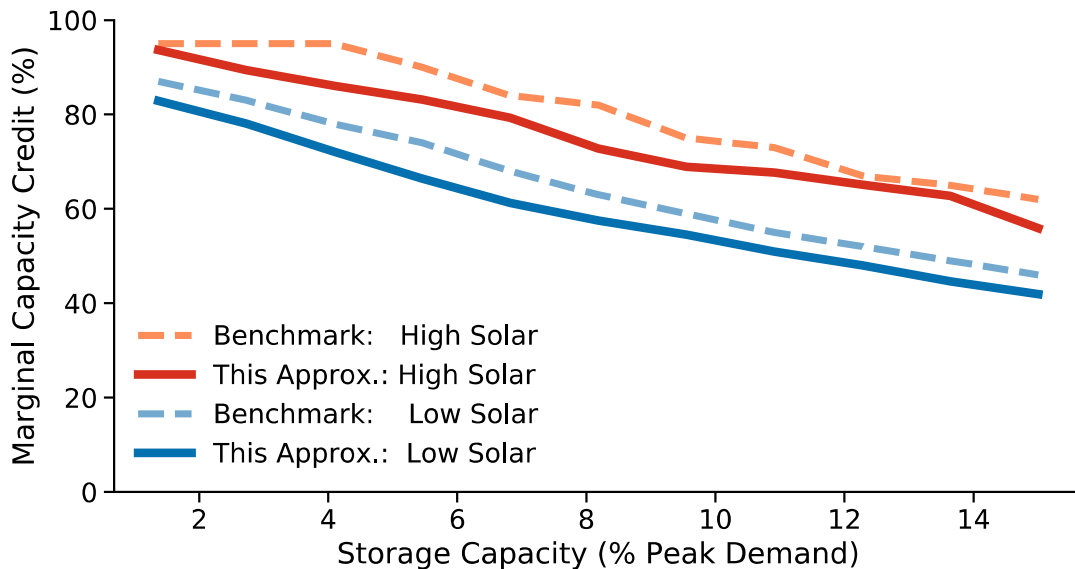


Figure 6. Comparison of the marginal capacity credit of 4h duration storage estimated with this method (This Approx.) to the effective load carrying capability calculated with a probabilistic method (Benchmark) for a western U.S. utility

The capacity credit with the algorithm in Section 2.1 is again directionally consistent and quantitatively similar to the ELCC benchmark. Both methods find the credit of 4-hour duration storage declines from an initial marginal capacity credit of 85-95% to a marginal capacity credit of about 40-60% as storage nameplate capacity increases to 15% of the utility’s peak demand. This decline occurs because the residual peak net demand gets broader as more storage is deployed. Reducing broader peaks require longer storage durations. Alternatively, deploying more storage with a fixed duration results in a lower

capacity credit. Both methods also show that the marginal capacity credit of storage is consistently 10-20 percentage points greater in the high solar scenario compared to the low solar scenario. This finding is consistent with results from Denholm et al. [42] which shows that high solar penetrations in California can narrow net load peaks and delay the decline in storage's capacity credit.

3.3 Case Study

The dispatch algorithm is used to evaluate the impact of different configurations on the capacity credit of solar + storage for JEA, a utility with similar peak demand levels in winter and summer, and FMPP, a utility whose demand is highest in the summer.

Using FMPP demand and solar data for 2012 along with the assumption that storage and PV both have a nameplate capacity of 100 MW, shows how a coupled solar + storage system can have a capacity credit less than that of an independent system (Figure 7a). In this particular case, the capacity credit of solar + storage is not impacted by configuration for short-duration storage (1 hour). Increasing the duration, however, produces a gap between the capacity credits of independent and coupled systems. The capacity credit of solar alone is 50 MW (50% of its nameplate capacity) and, with 4–5 hours of storage duration, the capacity credit of storage alone can exceed 90MW (90% of its nameplate capacity). Bringing these to resources together with a shared 100 MW inverter limits the capacity credit of the coupled solar + storage system.

Similar behavior is observed with the JEA demand and solar data, but here the difference between the capacity credit of the tightly and loosely coupled configurations is greater. In the tightly coupled case, the capacity credit of solar + storage can even be less than the capacity credit of storage alone (Figure 7b). The reason restricting charging to solar impacts the capacity credit in JEA may be that some of the JEA peak hours occur in the winter, when solar production is lower and less able to fully recharge storage during cold weather events that drive peak winter demand. In addition, demand peaks are wider for JEA than for FMPP; wider peaks require more energy, which is limited by solar generation in the tightly coupled case. At 6 hours of storage duration, requiring storage to only charge from solar (tightly coupled) results in the capacity credit that is less than that of storage alone (which can charge from the grid during off-peak hours).

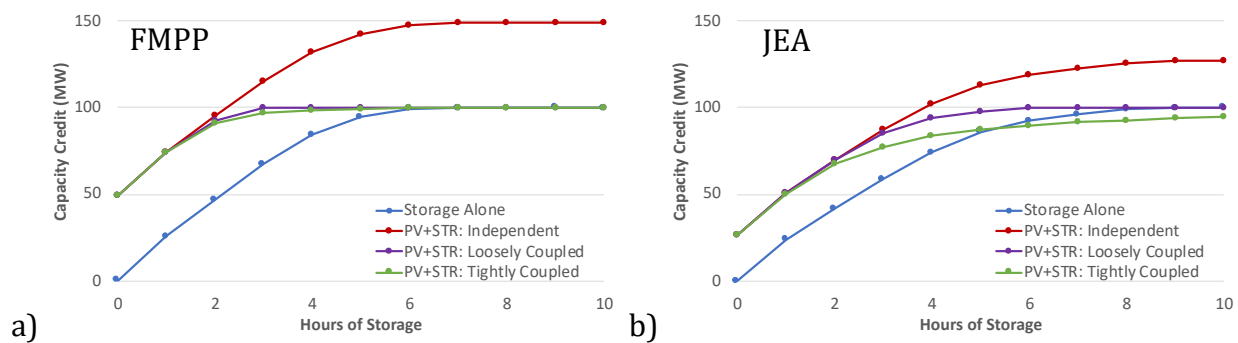


Figure 7. Variation in solar + storage capacity credit with different configurations with 100 MW storage and 100 MW of solar using 2012 demand and solar profiles from (a) the Florida Municipal Power Pool (FMPP) and (b) the Jacksonville municipal utility (JEA) .

In contrast, when storage size is reduced to only 20% of the solar nameplate capacity, the capacity credit of solar + storage is nearly equivalent across the independent, loosely coupled and tightly coupled configurations. With storage sized well below the inverter

capacity, and the capacity credit of solar less than 50% of its nameplate capacity, there are few opportunities for storage and solar to compete for limited inverter capacity. Likewise, in the tightly coupled case, a less energy is required to charge the smaller storage system, making storage easier to charge only with solar energy.

Even if storage and solar are equally sized, it may be possible to achieve the same (or similar) capacity credit with a coupled system as with an independent system if the inverter capacity is increased in the coupled system. This increases the cost of the coupled system, but it may be worth the cost if increasing resource adequacy is a high priority for the utility. The requirement to only charge storage from solar in the tightly coupled case may continue to be a limiting factor.

Ultimately, the optimal configuration of solar and storage depends on much more than maximizing the resource adequacy contribution [37]. Storage might reduce solar's levelized cost of energy, especially when the photovoltaic panels are oversized relative to the inverter, by charging coupled storage using energy that would otherwise be clipped. Storage can also provide additional value streams, including energy arbitrage and ancillary services. It can also smooth the solar production profile due to passing clouds. Future analysis could investigate how the different uses of storage alter the optimal solar + storage configuration and whether any of these other factors affect the capacity credit.

4. Conclusions

Many factors impact the capacity credit of solar and storage, including weather, utility demand profiles, solar and storage deployment levels, and the configuration of solar and storage systems. Exploratory analysis of the relative importance of different factors can be useful before evaluating specific cases via more detailed and resource-intensive modeling. The algorithm developed in this paper is a fast and relatively simple approach for identifying the dispatch that maximizes the capacity credit of storage and solar, suitable for such exploratory analysis.

Validation of the method shows that it mimics results from more detailed probabilistic methods, except for a very small utility with relatively large generators and widely distributed high-risk hours. Future analysis could more broadly investigate the circumstances that cause deviations from the benchmark based on probabilistic techniques.

Application of this method to data representing Florida utilities illustrates how it can improve upon rules of thumb used in practice. In particular, application of this method shows how, depending on the demand profile of the utility, the capacity credit of tightly coupled solar and storage can be less than the capacity credit of storage alone. This interaction is missed if utilities instead assume the capacity credit of solar + storage is the sum of the capacity credit of the independent components limited by the capacity of any shared equipment.

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