

Estimating the Capacity Value of Concentrating Solar Power Plants: A Case Study of the Southwestern United States

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Abstract—We estimate the capacity value of concentrating solar power (CSP) plants without thermal energy storage in the southwestern U.S. Our results show that CSP plants have capacity values that are between 45% and 95% of maximum capacity, depending on their location and configuration. We also examine the sensitivity of the capacity value of CSP to a number of factors and show that capacity factor-based methods can provide reasonable approximations of reliability-based estimates.

Index Terms—Capacity value, equivalent conventional power, concentrating solar power

I. NOMENCLATURE

T	index set for time
S	set of solar multiples (SMs) modeled
Λ	set of locations modeled
L_t	load in period t
G_t	conventional generating capacity available in period t
C_t	generating capacity available from the concentrating solar power (CSP) plant in period t
\bar{C}	nameplate capacity of CSP plant
B_t	generating capacity available from the benchmark plant in period t
Prob $\{X\}$	probability that the event X occurs
p_t	loss of load probability (LOLP) in period t
e	loss of load expectation (LOLE) without CSP or benchmark plant added to the system
e^C	LOLE with CSP plant added to the system
e^B	LOLE with benchmark plant added to the system
w_t	LOLP-based weight in period t
$v_{s,\lambda,Y}^r$	average annual equivalent conventional power estimate of CSP plant with SM of s at location λ using data from the set of years Y
$v_{s,\lambda}^f$	average annual capacity factor-based estimate of capacity value of CSP plant with SM of s at location λ

This work was supported by the U.S. Department of Energy through prime contract DE-AC36-08GO28308 and by the Alliance for Sustainable Energy, LLC through subcontract AGJ-0-40267-01.

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II. INTRODUCTION

AN issue that power system planners face is resource adequacy [1]. Although planners have a variety of generation technologies to choose from, there is increasing interest in the use of renewables. Some renewables can pose capacity planning challenges, however, due to the variable and uncertain nature of their real-time output [2]–[6]. Thus, accurate estimates of the capacity value of such resources are vital for planning purposes.

Due to excellent solar resource availability, the southwestern U.S. has great potential for concentrating solar power (CSP) plant development, with a number of plants currently operational. Table I lists these plants, of which only the Nevada Solar One plant includes thermal energy storage (TES), as well as their capacity and the type of CSP technology used. The plants for which data are available typically have capacity factors ranging from 20% to 25%. This paper applies reliability theory and the concept of equivalent conventional power (ECP) to estimate the capacity value of CSP plants without TES in the southwestern U.S. By studying a number of locations individually, we show that CSP plants can have ECPs that range between 45% and 95% of maximum capacity, depending on the plant’s configuration and location. We also examine the effect of load estimation errors, dry-cooled CSP, and subhourly weather variations on the capacity value of CSP. We further show that capacity value estimation techniques based on a CSP plant’s capacity factor can provide reasonable approximations of ECP. The remainder of this paper is organized as follows: section III surveys different capacity value estimation methods, including those that we examine; section IV details our case study, sections V through VII summarize our results and sensitivity analyses, and section VIII concludes.

III. CAPACITY VALUE ESTIMATION METHODS

A. Reliability-Based Methods and ECP

Reliability-based methods are a set of techniques used to estimate the capacity value of renewable and conventional generators [6]–[13]. These methods are based on two standard reliability indices—loss of load probability (LOLP) and loss of load expectation (LOLE). These indices measure the likelihood that outages may leave the system with insufficient capacity to serve the load. Conventional generator outages are typically modeled using an equivalent forced outage rate

TABLE I
LOCATION OF CSP PLANTS IN THE SOUTHWESTERN U.S. AS OF NOVEMBER, 2011

Plant Name	Location	Technology	Capacity (MW)
Solar Electric Generating Stations	Mojave Desert, CA	Parabolic Trough	353.8
Nevada Solar One	Boulder City, NV	Parabolic Trough	72
Kimberlina	Bakersfield, CA	Linear Fresnel Reflector	5
Sierra	Lancaster, CA	Power Tower	5
Maricopa Solar	Peoria, AZ	Stirling Dish	1.5

(EFOR), which captures the probability that a particular generator can experience a failure at any given time. With variable renewable generators one must model failures using an EFOR and capture resource variability. The latter is typically done using historical resource data or by simulating such data based on underlying probability distributions.

Reliability-based estimates include the effective load carrying capability (ELCC), equivalent firm capacity (EFC), and ECP methods. The ELCC of a generator is defined as the amount by which the system's loads can increase when the generator is added to the system, while maintaining the same system reliability (as measured by LOLE) [14]. The EFC of a generator, g , is defined to be the capacity of a fully reliable generator (*i.e.* with an EFOR of 0%) that can replace g while maintaining the same LOLE [15], [16]. A generator's ELCC and EFC will generally differ, since changing the generation mix of a system will change the distribution of the available capacity in a given hour whereas adjusting loads will not [13]. ECP is similar to EFC, except that the generator against which g is benchmarked is not fully reliable and thus has a positive EFOR [13]. This latter definition is especially attractive for a renewable generator since it allows the capacity value to be measured in terms of a dispatchable generator. For example, one may find that a 100 MW wind generator has a capacity value that is equivalent to a 30 MW natural gas-fired combustion turbine.

To express the ECP of a CSP plant one first defines the LOLP in period t of the base system without the CSP plant as the probability that the load in period t cannot be met by the conventional generators:

$$p_t = \text{Prob}\{G_t < L_t\}, \quad (1)$$

where the probability function implicitly accounts for the likelihood of generator outages and can also account for stochastic loads. The LOLE is defined as the sum of the LOLPs:

$$e = \sum_{t \in T} p_t, \quad (2)$$

and is typically computed over a year or a longer period.

The LOLE of the system when the CSP plant is added is:

$$e^C = \sum_{t \in T} \text{Prob}\{G_t + C_t < L_t\}, \quad (3)$$

where the probability function also accounts for variability in solar resource. The LOLE of the system when only the benchmark plant (*i.e.* without the CSP plant) is added is:

$$e^B = \sum_{t \in T} \text{Prob}\{G_t + B_t < L_t\}. \quad (4)$$

Since the CSP plant and benchmark unit add capacity to the system, by definition one always has that $e^C \leq e$ and $e^B \leq e$. The ECP of the CSP plant is found by adjusting the nameplate capacity of the benchmark generator until:

$$e^C = e^B. \quad (5)$$

Reliability-based methods are generally accepted as providing robust capacity value estimates, since they fully account for the effect of a generator on the reliability of a power system and have been applied to estimate the capacity value of solar photovoltaic (PV) and CSP plants [17]–[19]. With the latter, an ELCC method shows that a 100 MW CSP plant in Colorado would have a capacity value ranging between 65% and 81%. These methods require detailed system data, however, including EFORs of all of the generators, generator capacities, and loads. These methods have also historically been computationally expensive, since they can require computing system LOLPs multiple times to achieve the desired condition in equation (5), although this is less of an issue today [20].

B. Capacity Factor-Based Methods

Another popular approximation technique considers the capacity factor of a generator over a subset of periods during which the system faces a high risk of a shortage—for instance periods with high loads or LOLPs. A generator's capacity factor is defined as its average output during a set of periods divided by its nameplate generating capacity.

These techniques have been applied to wind [21], [22] and PV solar [23] and compared with reliability-based methods to assess their accuracy. Milligan and Parsons [3] compare a capacity factor-based approximation that uses the highest-load periods to other techniques that consider the LOLPs of the base system without added generation. One of the methods that they examine approximates the capacity value of wind as the average capacity factor during the highest-LOLP periods. Although loads and LOLPs are closely related, they are not necessarily perfectly correlated since generator capacities and EFORs can vary seasonally. Moreover planned maintenance outages and seasonal differences in water inflows to energy-limited hydroelectric generators can complicate the relationship between loads and LOLPs. If, however, such variations do not occur during the study period, then this method will give the exact same capacity value estimate as using the highest-load periods. They also consider a method in which the capacity value is approximated as a weighted average of the capacity factor of wind during the highest-load periods, with the LOLPs used as weights. This technique places higher weight on the capacity factor during periods

with high LOLPs. They apply these techniques considering between the top 1% and 30% of periods, and show that the approximation can approach reliability-based estimates if a suitable number of periods are considered. Their results suggest that using the top 10% of periods is typically sufficient.

These three estimation techniques can be applied to estimate the capacity value of a CSP plant. The highest-load and highest-LOLP methods approximate the capacity value as:

$$\frac{\sum_{t \in T} C_t}{|T| \cdot \bar{C}}, \quad (6)$$

where T is the set of either highest-load or -LOLP periods, and $|T|$ denotes the cardinality of T . The weights used in the LOLP-weighted approximation are:

$$w_t = \frac{p_t}{\sum_{t \in T} p_t}, \quad (7)$$

where T is the set of highest-load periods. The capacity value is then approximated as:

$$\frac{\sum_{t \in T} w_t \cdot C_t}{\bar{C}}. \quad (8)$$

Since only a subset of periods is considered and because the capacity factor is relatively easy to compute, these methods can reduce the computational burden of the estimation. Moreover, these types of estimation techniques and simpler heuristics are used by utilities and system operators to determine the capacity value of renewables for long-term capacity planning purposes. A recent North American Electric Reliability Corporation (NERC) report shows that most NERC system operators, with the exceptions of ERCOT, Midwest ISO, and Quebec Balancing Authority, use such approximation methods [24]. System LOLPs must be computed for the highest-LOLP and LOLP-weighted approximations, requiring conventional generator capacities and EFORs. However, the LOLPs must only be computed once, as opposed to in an iterative fashion as with reliability-based estimates.

IV. CASE STUDY

We estimate the ECP of CSP plants at five sites in the southwestern U.S., which are listed in Table II, using historical conventional generator, load, and weather data from 1998 to 2005. We study these locations in isolation (*i.e.* considering a CSP plant added to each site individually). Thus our ECPs are not additive, since they do not account for correlation in weather conditions between the locations. Moreover, our ECPs are calculated by assuming a single CSP plant is added and do not account for the fact that the marginal capacity value of CSP will be decreasing as more CSP capacity is added to the system. Our estimates also neglect transmission constraints, which can reduce the capacity value of CSP if there is insufficient capacity to deliver power to loads when LOLPs are high. Our estimates use hourly data, and in section VI-C we demonstrate that the ECPs are relatively insensitive to using subhourly data. This shows that hourly data are sufficient to capture the effect of solar resource variability on the capacity value of CSP.

TABLE II
LOCATION OF CSP PLANTS STUDIED

CSP Site	Coordinates
Arizona	32.57° N, 112.45° W
Death Valley California	36.03° N, 117.45° W
Imperial Valley California	33.65° N, 116.05° W
Nevada	36.55° N, 116.45° W
New Mexico	34.35° N, 107.35° W

A. CSP Model

We analyze parabolic trough CSP plants, although our approach can be generalized to study other CSP technologies. CSP plants consist of two separate but interrelated parts: a solar field, which collects solar thermal energy, and a powerblock, which uses a heat engine to convert the thermal energy into electricity. CSP plants can also include TES, which we exclude from this discussion since we focus on CSP plants without TES. These components can be sized differently, which will affect the operation and capacity value of the plant. The size of the powerblock is typically measured based on its rated output, measured in MW of electricity (MW-e). The size of the solar field can be measured by the area that the field covers or by using the concept of the solar multiple (SM) [25]. A solar field with an SM of 1.0 is sized to provide sufficient thermal energy to operate the powerblock at its rated capacity with direct normal irradiance (DNI) of 950 W/m², a wind speed of 5 m/s, and an ambient temperature of 25° C. Because the SM allows the solar field to be scaled in relation to the powerblock size, we hold the powerblock capacity fixed and consider CSP plants with different SMs.

We simulate CSP generation using the model developed by Sioshansi and Denholm [26], which is based on the Solar Advisor Model (SAM). SAM is a software package that uses detailed weather data to model the dynamics of a solar field. SAM has been validated against empirical CSP data from the Solar Electric Generating Stations [27]. The thermal energy collected by the solar field, as modeled by SAM, is input to a mixed-integer programming (MIP) model to optimize the dispatch of the plant. The MIP model assumes that the components and performance of the CSP plant correspond to the default trough system modeled in version 2.0 of SAM [25]. This plant has a 110 MW-e powerblock, which can be operated at up to 115%, a two-hour powerblock minimum uptime, non-linear component parasitics, and no auxiliary fossil-fueled heat source. When the parasitic component loads are taken into account, the maximum net electric output of the CSP plant is about 120 MW-e. The default trough system has an EFOR of 6%, which we assume.

B. Data Sources

Since the locations that we study are in the Western Electricity Coordinating Council (WECC) region, we model the entire WECC to determine LOLPs and LOLEs. Since we use the same underlying system in our calculations, ECP differences between the locations are solely due to solar resource differences. System planners often use more limited regions in capacity planning, however. Because the capacity value of CSP depends on the relationship between LOLPs and

solar availability, the capacity value of a CSP plant may differ depending on whether a more limited study region is used.

WECC LOLPs are estimated by calculating the system's capacity outage table, which assumes that generator outages follow Bernoulli distributions that are serially and jointly independent [7]. Data requirements and sources used in our calculations are outlined below.

1) *Conventional Generators*: The rated capacities of conventional generators are obtained from Form 860 data collected by the U.S. Department of Energy's Energy Information Administration. Form 860 reports winter and summer capacities for each generator, which we use in our analysis. The WECC had between 1,016 and 1,622 generating units and 123 GW and 163 GW of generating capacity during the years that we study. This reflects load growth between the years 1998 and 2005.

We model generator outages using a simple two state (online/offline) model. We use the NERC's Generating Availability Data System (GADS) to estimate generator EFORs. The GADS specifies historical annual average EFORs for generators based on generating capacity and technology, which we combine with generating technology data given in Form 860. The EFORs used range between 2% and 17% and have a capacity-weighted average of 7%. The benchmark unit we use in the ECP calculation is a natural gas-fired combustion turbine, and we use an EFOR of 7% based on the GADS.

2) *Load*: Hourly historical load data for each year are obtained from Form 714 filings with the Federal Energy Regulatory Commission. Form 714 includes load reports for nearly all of the load-serving entities (LSEs) and utilities in the WECC, although some small municipalities and cooperatives are not included. We assume loads are fixed and deterministic based on these data, which have annual peaks ranging between 107 GW and 124 GW. Since the system loads increase over time and capacity expansion can lead or lag such growth, we adjust the hourly load profiles in each year individually so the base system (*i.e.* without the CSP or benchmark plant added) has an annual LOLE of 2.4. This corresponds to the standard planning target of one outage-day every 10 years [28]. This load adjustment is done by scaling all of the hourly loads by a fixed percentage, ranging between 0.1% and 5% in the different years. One additional issue with these data is that LSEs do not always properly account for daylight savings time (DST) in their load reports. Section VI-A describes a sensitivity analysis in which we shift all loads forward and backward one hour to bound the effect of misreported load data on the ECPs.

3) *Weather*: SAM requires detailed weather data, including DNI, dry-bulb and dew-point temperatures, relative humidity, barometric pressure, and wind speed. These data are obtained from the National Solar Radiation Data Base [29], which accounts for cloud cover and other factors in determining local weather conditions.

V. ECP ESTIMATES

Fig. 1 summarizes the average (over the eight years studied) annual ECP values. The ECP values are normalized by the

120 MW-e maximum net output of the CSP plant. The figure shows that the solar field size has a direct impact on the ECP. This is because a CSP plant with a small field will often operate below its rated capacity, reducing its ECP. As the field size increases, more thermal energy will be available during such hours, increasing the ECP. On the other hand, a large solar field incurs greater capital costs and excess thermal energy that would overload the powerblock will be wasted [26]. For these reasons, CSP plants without TES have historically been built with SMs of less than 1.5. Fig. 1 also shows that the rank ordering of the locations, in terms of ECP, can vary as a function of solar field size. This is because adjusting the solar field size will change the operation of the plants. In some cases increasing the SM will allow the powerblock to startup during a high-LOLP hour, when it would otherwise not be able to with a smaller solar field due to minimum-load constraints on the powerblock.

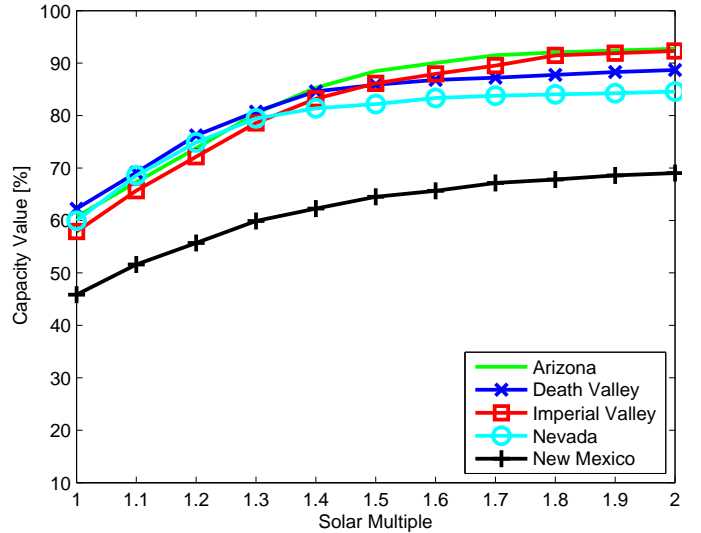


Fig. 1. Average (over the years 1998 to 2005) annual ECP of a CSP plant, as a percentage of 120 MW-e maximum net output of the plant.

Fig. 2 shows annual ECPs at the New Mexico location, and demonstrates that there can be significant interannual variability in the capacity value. For instance with an SM of 1.0 the ECP of the plant in the year 2000 is more than four times greater than that in 2004. Comparing the operations of the plant during high-LOLP hours in these two years illustrates the cause of these differences. In the year 2000, the highest-LOLP hours occur on 1 August. Fig. 3 shows hourly LOLPs and generation from the New Mexico plant with an SM of 1.0 on this day. The CSP plant has an average output of about 85 MW-e during the high-LOLP hours, and this coincidence between CSP generation and LOLPs yields the high ECP in 2000. Fig. 4 shows the hourly DNI and load data on this day, which are also coincident. This coincidence is common in many parts of North America, including the WECC, which have summer peak loads that are driven by cooling needs that will be correlated with solar availability.

The highest LOLPs in 2004 occur on 10 August. Fig. 3 shows hourly CSP generation and LOLPs on this day. The output of the CSP plant is significantly less coincident with

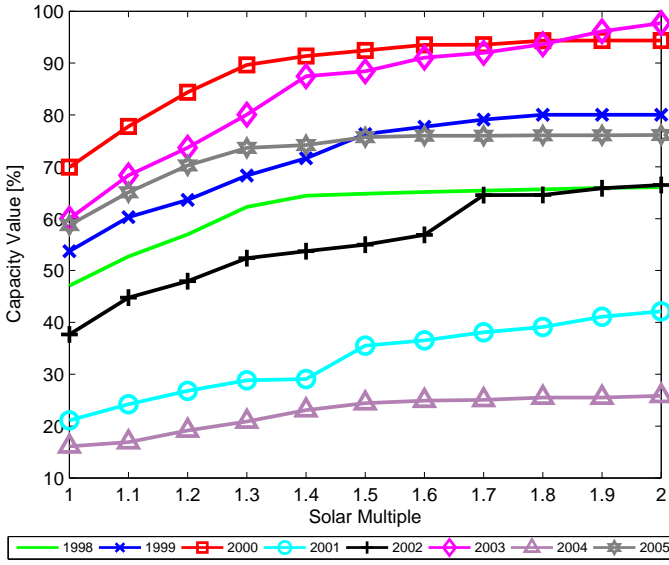


Fig. 2. Annual ECP of a CSP plant at the New Mexico location, as a percentage of 120 MW-e maximum net output of the plant.

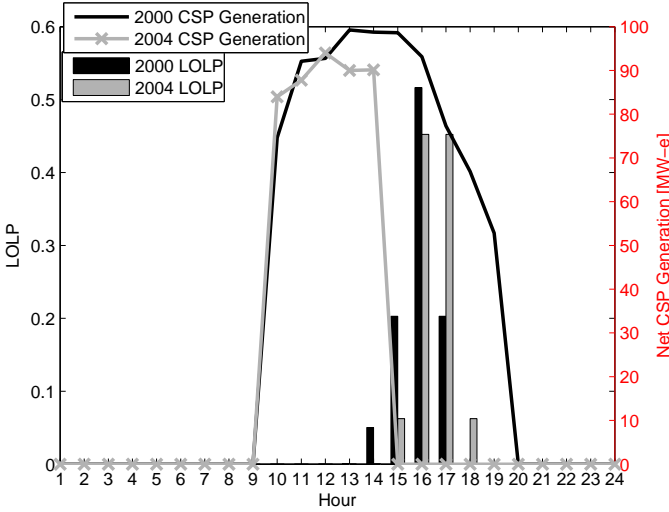


Fig. 3. Hourly LOLPs and generation from a CSP plant at the New Mexico location with an SM of 1.0 on 1 August, 2000 and 10 August, 2004.

the LOLPs and drops off in hour 15 when the LOLPs increase, giving the lower ECP in this year. Fig. 4 shows the diurnal DNI pattern on this day and illustrates why the output of the CSP plant falls in this way—the sharp decrease in DNI in hours 15 and 16 forces the CSP plant to shutdown due to its minimum-load constraint. Although DNI increases in hour 17, the powerblock cannot startup due to its two-hour minimum up-time constraint. These findings point to the fact that solar resource and loads will not be perfectly correlated, even in the summer. This is because ambient temperatures can be high even with cloud cover.

These findings also show that CSP capacity values are highly system specific—many European systems, for instance, have winter or night peaks, which could lower ECPs. TES could provide added value in such systems since it could allow solar energy to be shifted to the peak. Future changes in diurnal or seasonal load patterns could also affect ECPs.

Perez *et al.* [18] study the relationship between the capacity value of PV and the ratio of the summer to winter peak load of a system. By examining systems with different ratios they are able to show the sensitivity of the capacity value to this ratio. While such an approach may be useful for CSP, it does not provide meaningful results for our case study since we estimate capacity values using the same underlying system during a set of years which had little change in the ratio of the load peaks.

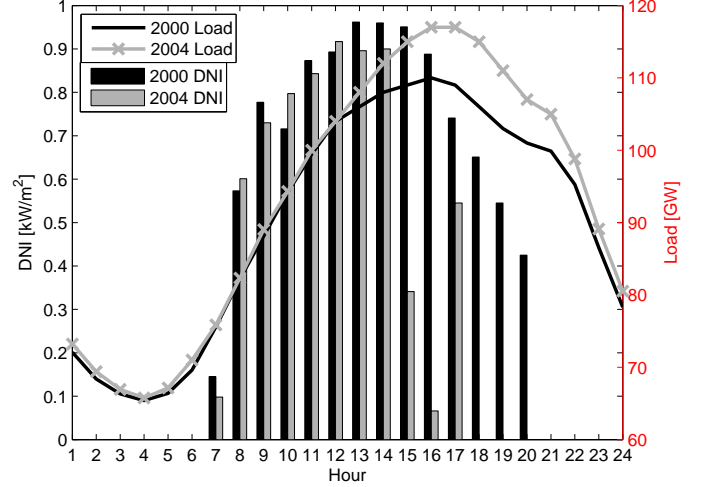


Fig. 4. Hourly DNI and load on 1 August, 2000 and 10 August, 2004.

The interannual variability in ECPs illustrates that several years of data are required to provide a robust capacity value estimate, as has been shown with conventional generation and wind [8], [20]. Table III further demonstrates this by summarizing the average root mean squared error (RMSE) between the average ECP using all eight of the years studied and a subset of the data. This RMSE metric is defined as:

$$\sqrt{\frac{1}{|S| \cdot |\Lambda|} \sum_{s \in S} \sum_{\lambda \in \Lambda} (v_{s,\lambda,Y'}^r - v_{s,\lambda,Y}^r)^2}, \quad (9)$$

where Y is the full set of eight years studied and Y' is a subset of these years. Thus the quantity, $v_{s,\lambda,Y'}^r - v_{s,\lambda,Y}^r$, is the difference in the ECP when a subset as opposed to all eight years of data are used. The RMSE is averaged over the different possible sets of consecutive years of data that can be used. For instance, if six years of data are used the ECP can be computed using data from 1998-2003, 1999-2004, or 2000-2005, and the average of three corresponding RMSEs are reported in the table. The table demonstrates that using more data provides a more accurate ECP estimate. It can also be used to weigh the costs of gathering additional system data against increased ECP estimate accuracy.

VI. SENSITIVITY OF ECP

A. Sensitivity to Load Errors

An issue with the loads used in our analysis is that some utilities do not account for DST when reporting Form 714 data. Thus it is possible that the simulated output of the CSP plants could be offset from actual loads and LOLPs.

TABLE III
AVERAGE ROOT MEAN SQUARED ERROR BETWEEN ECP ESTIMATES
USING ALL EIGHT YEARS AND A SUBSET OF THE DATA

Years Used	RMSE
1	13.3
2	9.4
3	6.4
4	5.5
5	4.7
6	3.1
7	0.8

To bound the effect of such misreporting, we calculate ECPs with all of the system loads shifted one hour forward and backward. Fig. 5 shows the resulting ECPs for the Imperial Valley location, which can be up to 5% less than the ECPs with unshifted loads. We observe similar results at the other locations. The fact that the ECP drops regardless of whether the load is shifted forward or backward suggests that most of the loads reported in Form 714 are correct. This is because solar resource and CSP generation will have some correlation with system loads, and this correlation is maximized when the loads are not shifted.

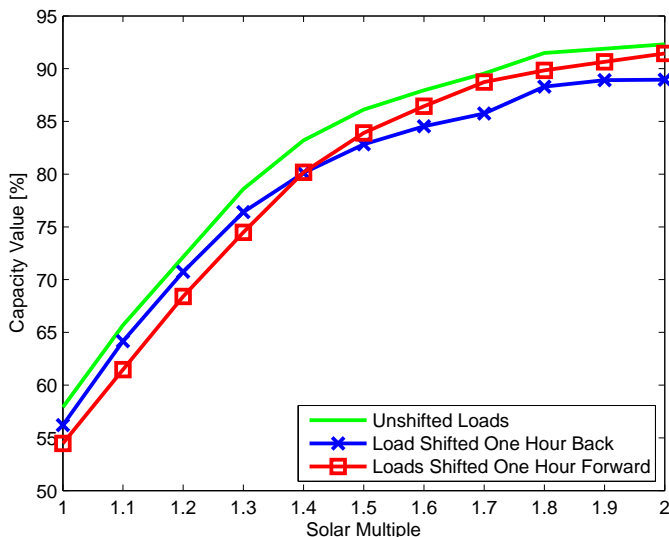


Fig. 5. Average (over the years 1998 to 2005) annual ECP of a CSP plant at Imperial Valley location with loads shifted, as a percentage of 120 MW-e maximum net output of the plant.

B. Sensitivity to Powerblock Dry Cooling

The default CSP plant configuration modeled in SAM assumes a wet-cooled powerblock. Although the currently operational CSP plants listed in Table I are wet-cooled, this may not be a feasible option going forward, given the arid conditions of the southwestern U.S. Indeed, a number of CSP plants under development will be dry-cooled. Dry cooling can reduce the powerblock efficiency, which will reduce CSP generation, especially at high ambient temperatures. We model a dry-cooled CSP plant by including a factor in the MIP model that accounts for these efficiency losses in computing the net electrical output of the CSP plant [26].

The annual net generation of a dry-cooled plant is between 1% and 8% lower than a wet-cooled one, depending on location and SM. The New Mexico location suffers the least from dry cooling, with less than a 1.8% reduction, whereas the Arizona sees an up to 8.4% generation drop. Fig. 6 shows the average annual ECP of the dry-cooled CSP plants. Comparing this to Fig. 1 shows that dry cooling will have a much greater impact on capacity value than the change in generation suggests, with between an 8% and 17% ECP reduction. This is because the effect of dry cooling on CSP output will be concentrated during high-temperature hours, which also tend to be high-load hours. Fig. 6 may overstate the effect of dry cooling on capacity value, however. This is because if dry-cooling systems are designed for summer high-temperature conditions, the impact to CSP generation and capacity value can be reduced [30]. A full cost and performance analysis would be necessary to determine an optimal design for such a system.

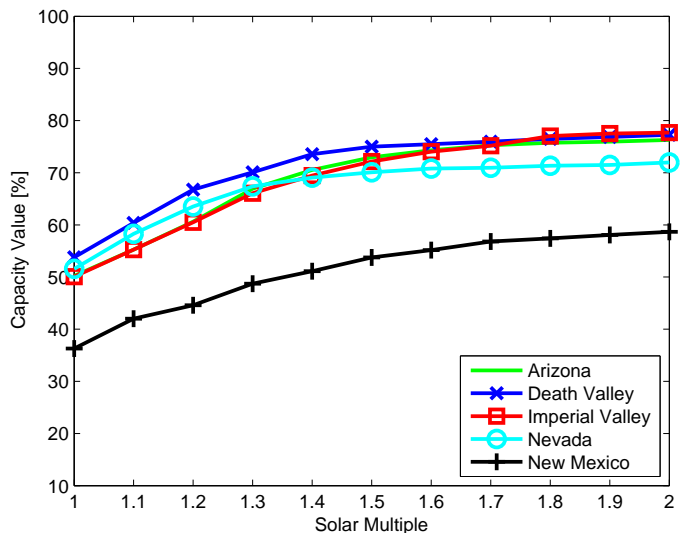


Fig. 6. Average (over the years 1998 to 2005) annual ECP of a dry-cooled CSP plant, as a percentage of 120 MW-e maximum net output of the plant.

C. Sensitivity to Subhourly Weather Variability

Although our ECP estimates use hourly weather data, these parameters can have non-trivial subhourly variation, for instance due to passing cloud cover. While subhourly DNI variability can impact the capacity value of CSP, it may only have a limited effect since the heat-transfer fluid (HTF) of the plant has thermal inertia, which can maintain some electrical output during brief DNI reductions.

To determine the effect of subhourly DNI variability on the capacity value of CSP, we compare ECPs calculated using one-minute and hourly weather data. We model the operation of the CSP plant using the same SAM- and MIP-based model, which is adapted to model one-minute operations by appropriate scaling of the variables and parameters. SAM accounts for HTF thermal inertia in computing the solar energy collected by the solar field, and this is captured in greater detail in the one-minute model.

We use one-minute weather data, obtained from the University of Nevada, Las Vegas, from the year 2007 for a location in Boulder City, Nevada.¹ We also use the one-minute model with hourly averages of the weather data to represent a case in which hourly weather data are used to model CSP generation. We compute ECPs using the one-minute generation data and hourly WECC loads. Since the underlying modeling technique and load and conventional generator data are identical between the two cases, any differences in the ECP estimates are solely due to the use of one-minute weather data as opposed to hourly averages.

Fig. 7 shows these ECPs and demonstrates that using hourly-average data provides a close approximation of the ECP obtained with one-minute data—the maximum difference is 1.5%. Using hourly-average data overestimates the ECP for most SMs, since subhourly DNI variations can keep the powerblock from running above its minimum operating point. These effects are not fully captured when the one-minute data are averaged. Nevertheless, the small ECP differences suggest that hourly data can provide relatively good capacity value estimates if subhourly data are not available (or too computationally expensive to work with). This has also been shown for wind [20].

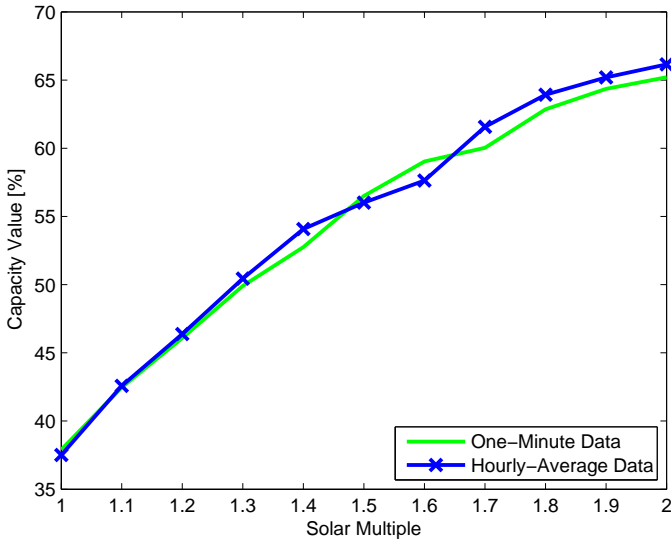


Fig. 7. ECP of a CSP plant at Boulder City, Nevada location in 2007 using one-minute and hourly-average weather data, as a percentage of 120 MW-e maximum net output of the plant.

VII. CAPACITY FACTOR-BASED APPROXIMATIONS

Fig. 8 shows the average (over the eight years studied) annual ECPs at the Imperial Valley location, as well as capacity factor-based approximations. The figure shows the top-load, top-LOLP, and LOLP-weighted approximations and considers cases in which the top-10 and top-100 hours of each year are used. The figure shows that the LOLP-weighted method provides the best approximation of the ECP, although the approximations are all biased slightly downward by between

¹The site is around the Nevada One CSP plant and is at coordinates 35.80° N, 114.97° W.

7% and 9%. The figure also shows that using the top-10 hours provides a better approximation than using the top-100.² This illustrates that the capacity value of CSP is highly sensitive to the most critical hours of the year. This is due to the strong correlation between system loads and CSP generation—adding more hours to the calculation reduces the approximated value, biasing the result. Conversely, a capacity factor-based approximation of the capacity value of wind requires the top-10% of the periods of the year to be considered [3]. Wind requires significantly more periods to be included because of the much weaker correlation between system loads and wind generation. Thus a greater number of periods must be included, otherwise the approximation will be biased downward.

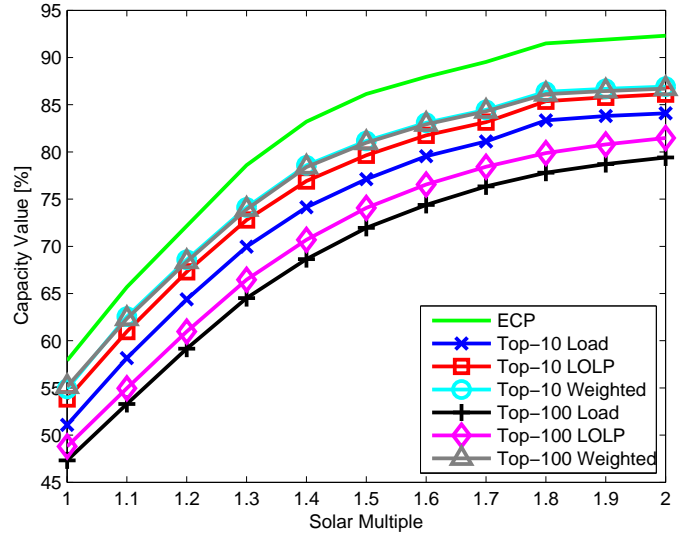


Fig. 8. Average (over the years 1998 to 2005) annual ECP and capacity factor-based approximations of a CSP plant at Imperial Valley location, as a percentage of 120 MW-e maximum net output of the plant.

Table IV summarizes the RMSE of the capacity factor-based approximations compared to the ECP for all of the locations studied. This RMSE metric is defined as:

$$\sqrt{\frac{1}{|S| \cdot |\Lambda|} \sum_{s \in S} \sum_{\lambda \in \Lambda} (v_{s,\lambda}^r - v_{s,\lambda}^f)^2}. \quad (10)$$

The table shows that using the top-10 hours and the LOLP-weighted method provides the best approximation of the ECP.

TABLE IV
AVERAGE ROOT MEAN SQUARED ERROR OF CAPACITY FACTOR-BASED APPROXIMATIONS OF ECP

	Top-Load	Top-LOLP	LOLP-Weighted
Top-10 Hours	8.47	7.65	4.65
Top-100 Hours	11.14	9.85	5.34

VIII. CONCLUSIONS

This paper analyzes the capacity value of CSP plants without TES at a number of locations in the southwestern U.S. By examining these locations in isolation, we show that CSP

²Moreover, capacity factor-based approximations using the top-10% load and LOLP hours yield even worse results than those using the top-100 hours.

plants with SMs between 1.3 and 1.5, which are the most likely configurations for plants without TES, can have ECPs between 60% and 88% of maximum capacity, depending on location. This is because summer cooling loads and LOLPs tend to be correlated with solar resource. Although the majority of existing CSP plants and plants under development do not include TES,³ the technology is viable and would increase capacity values by allowing generation to be shifted when this coincidence is not perfect. Thus evaluating the benefit of TES in improving the capacity value of CSP is an important area of future research.

As with other renewables, CSP capacity values can have significant interannual variation, and multiple years of data are needed to provide robust long-term estimates. Our analysis also examines the sensitivity of the ECP to a number of factors. Importantly, we show that subhourly DNI variations have a small effect, suggesting that hourly data are sufficient for capacity value estimation. This is largely due to the thermal inertia of a CSP plant meaning that even without TES the type of CSP plant considered here has the ability to ride through brief cloud cover, which is a potentially important difference between CSP and other solar technologies, such as PV.

We also examine the use of capacity factor-based methods and show that while these tend to be biased downward, they can provide reasonable ECP approximations. This is especially useful given the use of such approximations by system operators [24]. Although we use a standard method for estimating LOLPs, more complex techniques have been developed and warrant further research. This includes modeling load uncertainty, using Markovian failure models that capture serial correlation in generator failures and repairs, and seasonally varying EFORs that capture planned outages and hydrological conditions for hydroelectric generators.

Although we estimate ECPs by modeling the entire WECC system, system planners often use a more limited system footprint. This could affect the ECPs, depending on the extent to which solar resource is coincident with the ‘local’ system load. By modeling the entire WECC system we also assume that the system has sufficient transmission capacity to deliver power wherever it is needed. If binding transmission constraints prevent this, actual ECPs could be lower than our estimates [24].

Our results capture the ECP of CSP in the near-term under current market conditions, since we neglect a number of issues that are currently not pertinent but can affect CSP in the future. Future changes in the generation mix, especially higher solar penetrations, can affect ECPs. This is because the peak of the net system load can be affected by changes in the generation mix, potentially reducing the ECP of CSP. Perez *et al.* [18] demonstrate this in the case of PV. Similarly, as more CSP is added to the system the marginal capacity value of added CSP should diminish. TES should help to alleviate this issue, since it adds flexibility to shift generation to serve the peak of the net system load. This diminishing marginal capacity value of

CSP is unlikely to be a pressing issue for some time, however, since the 21 CSP plants under development in the U.S. will amount to less than 4 GW of generating capacity. Moreover, our analysis considers the locations modeled in isolation and without considering the effects of weather correlation on the capacity value of a portfolio of generators. Thus our ECP estimates are likely non-additive. If properly sited, geographic diversity could improve the overall ECP of a portfolio of CSP plants, since the correlation in real-time solar resource can be weaker between dispersed locations. This could yield an output profile from the plants that is more constant and better capacity values, as has been shown for wind [4]. This benefit, again, requires a strong transmission system, but the value of such an optimized portfolio of CSP resources is an open question that requires further research.

ACKNOWLEDGMENT

The authors would like to thank M. Mehos, C. Turchi, M. Milligan, A. Green, W. Short, R. Newmark, A. Sorooshian, A. Conejo, the associate editor, and seven anonymous reviewers for helpful discussions and suggestions.

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³The National Renewable Energy Laboratory maintains a list of CSP plants in the U.S., which is available at <http://www.nrel.gov/csp/solarpaces/>. As of November 2011, it lists 21 plants in various stages of development, of which only four include TES.

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