EVALUATION OF PV GENERATION CAPACITY CREDIT FORECAST ON DAY-AHEAD UTILITY MARKETS

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ABSTRACT

Following a successful preliminary evaluation of the NDFD-based solar radiation forecasts for several climatically distinct locations, the evaluation is now continued by testing the forecasts' end-use operational accuracy, focusing on their ability to accurately predict the effective capacity of grid-connected PV power plants. The predicted and actual utility peak load reduction performance of PV power plants are compared for two case studies: ConEdison in New York City, and Sacramento Municipal Utility District, in California

1. BACKGROUND

The effective capacity quantifies a power plant's ability to provide adequate power generation at critical load demand times. Several studies by Perez et al. (1998, 2006) have found the effective capacity of PV to be high when load demand is driven by commercial air conditioning. However skepticism still prevails among grid operators because the output of PV power plants cannot be controlled or dispatched. Grid operators would be more comfortable if capacity could be ascertained operationally by knowing in advance what the output of solar power plants would be, particularly when the grid is expected to be strained from high demand.

This need to know power plant output in advance is not limited to PV: indeed a large proportion of wholesale electric power transactions are made on the day-ahead market. On this market, energy producers bid in advance for the sale of electric power as a function of time of day. Stiff penalties occur if a producer fails to deliver.

PV forecasts will be of importance to both power generators and grid operators, because (1) a growing grid-connected PV base will affect the day-ahead market by modifying the load demand forecast; and (2) some PV operators may be interested in taking part in the day-ahead market. Both arguments become critical during times of peak demand when the grid is stressed and when energy values and penalties are very high, hence the importance of properly ascertaining forecasted PV capacity.

2. APPROACH

Through two exploratory case studies, we evaluate the accuracy of predicting the effective capacity of PV, on a day-ahead and a two-days-ahead basis, by comparing after-the-fact and forecasted effective capacities

The two case studies include New York City, NY, for the summer of 2006, and Sacramento, CA, for the summer of 2005. The utilities servicing both cities -- respectively Consolidated Edison (ConEd) and Sacramento Municipal Utility District (SMUD) -- are summer-peaking, and therefore, experience maximum grid stress and high price conditions during the selected summer time period.

For New York City we have access to both actual loads and load forecasts (NYISO, 2006). Forecasted PV outputs are derived from the NOAA cloud cover forecasts (NDFD, 2005-6). After-the-fact PV data are simulated using time/site specific satellite-derived irradiances (Perez et al., 2002). We can thus compare operational forecast conditions – i.e., using forecasted loads and forecasted PV output – against after-the-fact situations – i.e., using actual loads and satellite-derived PV data. In addition, we can decouple the uncertainty of solar radiation and load forecasts by analyzing forecasted conditions when load is ideally predicted – i.e., using forecasted PV but actual loads.

For Sacramento, we only have access to actual load data (Obadiah, 2005). So the comparison focuses solely on the accuracy of the solar forecasts, removing the uncertainty of the load forecasts.

3. METHODOLOGY

3.1 Defining Effective Capacity Metrics

The effective capacity of PV is quantified using two metrics:

1. Effective Load Carrying Capability (ELCC): The ELCC of a power generator represents its ability to effectively increase the generating capacity available to a utility or a regional power grid without increasing the utility's loss of load risk. For instance, a utility with a current peaking capability of 2.5 GW could increase its peaking capability to 2.55 GW with the same reliability by adding 100 MW of new generation, provided the ELCC of the new generation is 50 MW, or in relative terms, 50%. As described by Garver (1966), the ELCC may be extracted from time series of [forecasted] load and power generation – here PV generation – data.

2. Solar Load Control (SLC): This metric answers the two following questions: (1) how much energy backup (e.g., from load management) would be necessary, cumulatively over an entire peak demand season, to guaranty a PV effective capacity of 100%; and (2) how much more backup energy would be required to accomplish the same task without PV? A visual representation of the SLC metric is shown in Fig. 1.

Effective capacity is a function of both PV penetration within the considered power grid, and PV array orientation and tilt. For this study, we investigated penetration levels ranging from 2% to 20%. For all simulations, we selected a stationary PV configuration well suited to match mid-afternoon peak demand: facing southwest with a slope of 30°.

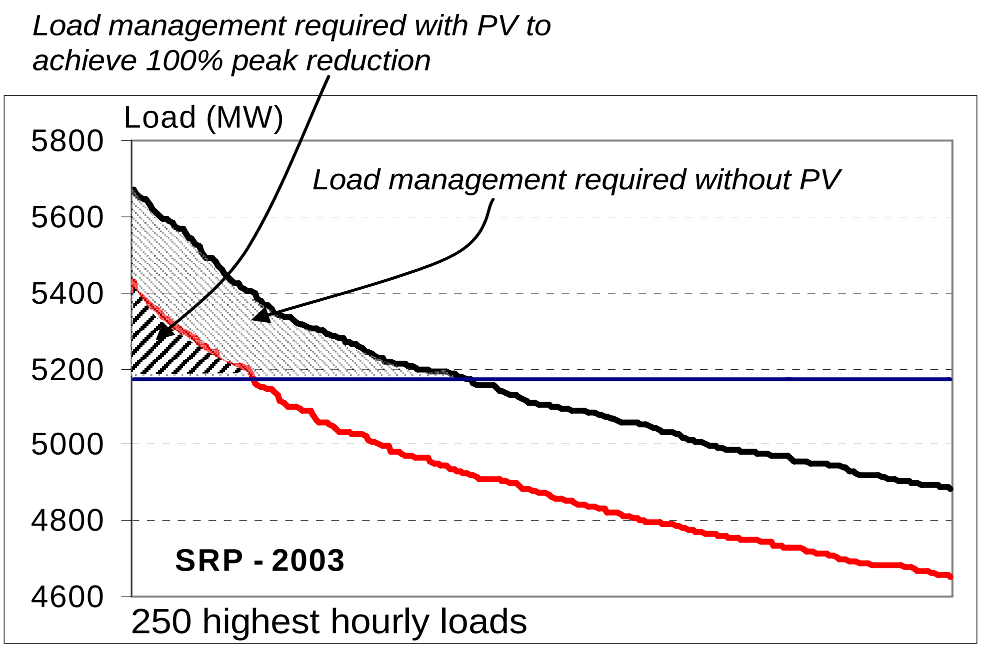

Figure 1: Utility load durations curves typically consist of one year worth of hourly loads sorted from highest to lowest. The peak region of the curves provides information on peaking generation requirements and utilization. The example above (for Salt River Project in 2003) shows load duration curves without PV and with simulated PV at 10% penetration. The light shaded area represents the load control required to reduce peak generation by 500 MW without PV. The heavy shaded area represents the amount of SLC required to accomplish the same goal with PV.

3.2 Experimental Data

Forecasted hourly PV outputs are simulated from forecasted hourly irradiances using the program PVFORM (Menicucci & Fernandez, 1988). Forecasted hourly irradiances are derived from 3-hourly irradiance forecasts via time extrapolation at constant clearness index, kt' (Perez et al., 1990). The 3-hourly irradiance forecasts are modeled from the gridded NDFD's 3-hourly cloud amount forecasts (NDFD, 2005.6) using the methodology previously presented by Perez et al. (2005 and 2006).

Actual (after-the-fact) PV outputs are simulated from satellite-derived hourly

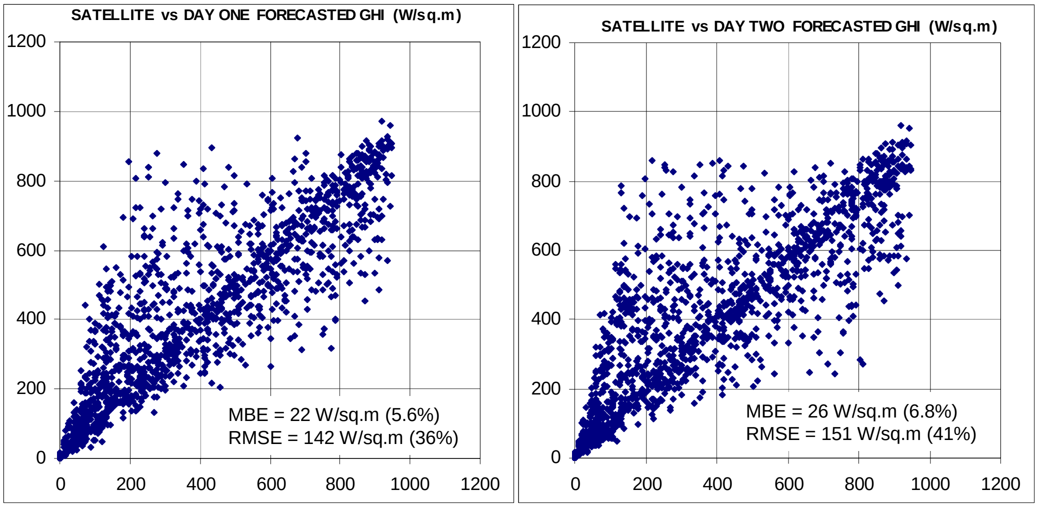

Figure 2: One- and two-day forecasts vs. actual (satellite-derived) GHI in New York City (summer 2006)

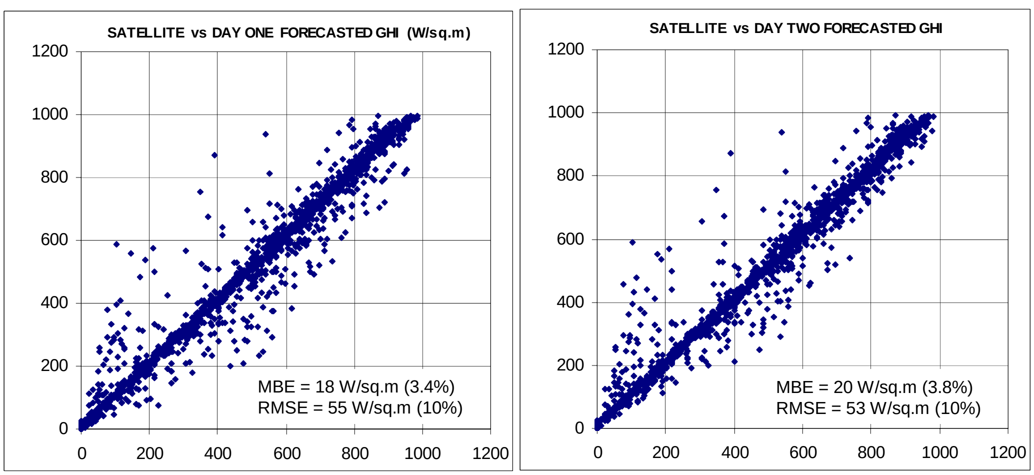

Figure 3: One- and two-day forecasts vs. actual (satellite-derived) GHI in Sacramento (summer 2005)

irradiances. The satellite methodology and its accuracy have been presented and discussed in detail in several publications (Perez et al., 2002 and 2004).

Actual hourly loads for the city of New York were obtained from the New York Independent System Operator (NYISO, 2006). Sacramento load data were obtained courtesy of SMUD (Obadiah, 2005).

Forecasted load data archives for the Sate of New York are publicly available and downloadable from the NYISO web site (NYISO, 2006).

All data sets for New York cover a period from May 22 through September 5, 2006. Data for Sacramento are from June 27 through October 31, 2005.

4. RESULTS

1. Overall irradiance Forecast verification

The accuracy of next-day and two-day global irradiance forecasts for all data points during the considered time period is illustrated in Fig. 2 for New York and Fig. 3 for Sacramento. Note, again, that satellite-derived irradiances are used "ground-truth" for the forecasts.

Results are fully consistent with previous evaluations both in terms of scatter and bias. Errors are comparable despite the added noise of extrapolation from 3-hourly to hourly time series. Note that forecasts are remarkably good in Sacramento with 10% RMSE during the largely clear summer season

2. Overall utility load forecast verification

Actual and forecasted hourly loads are compared in Fig. 4. This comparison is only available for New York City where we have access to both load and load forecast data. Load forecasts which are constantly fine-tuned by grid-operators are expectedly more accurate overall than solar forecasts; moreover, load forecasts depend first and foremost on temperature forecasts – better mastered than cloud amount forecasts – and, because of the inertia of load demand

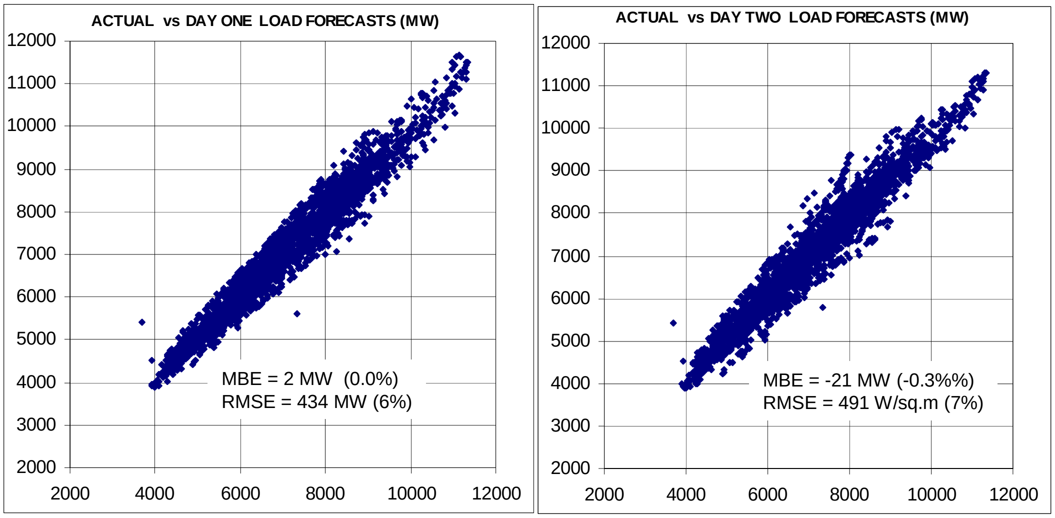

Figure 4: One- and two-day load forecasts vs. actual loads for New York City (summer 2006)

spanning several days, also depend on known current and past information.

3. <u>Capacity forecast verification using ideal load forecasts</u>

Because capacity is determined by the ability of PV to deliver during critical peak hours, the accuracy of the forecast during these critical events is the most relevant benchmark, regardless of overall accuracy.

Here, we focus solely on the solar forecast performance, using actual load data (i.e., assuming that loads are ideally forecasted). The results for ELCC are presented in Table 1 for NYC and Sacramento. SLC results are in Table 2.

Both forecasted capacity credit metrics are very close (within 1-2%) to the values obtained after the fact.

4. <u>Operational capacity forecast evaluation</u>

In this evaluation context we can fully assess the operational forecast accuracy – but only in New York – by using both forecasted loads and solar forecasts. The results for the ELCC and SLC capacity metrics are given in Table 3 and Table 4, respectively. Forecasts are close to the after-the-fact values, but the accuracy is not nearly as good as when the load is ideally predicted. For both metrics, the load forecast is a larger source of capacity credit prediction error than the solar forecasts

5. DISCUSSION

The overall accuracy of hourly solar forecast observed in this study is consistent with, and confirms previous assessments: Little bias, and dispersion ranging from the low 10% for clear sites to 30-35% for partly cloudy climates.

The critical [peak demand time] solar forecasts are satisfactory and lead to predicted capacity credit values which are very close to achieved values. It is interesting to remark that in New York, the load forecasts turn out to be a larger source of prediction error than the solar forecasts, despite a much better overall accuracy. This observation may be indicative of the fact that, because the sun indirectly drives peak demand, the load will naturally tend to match the solar forecast error (e.g., if the forecasted irradiance is too high, the load will likely be lower than predicted, leading to a predicted capacity credit value close to the forecast).

The results of these study should, of course be confirmed with larger data samples. Nevertheless, the evidence presented here suggests that solar forecasts could be used effectively to manage solar resource on the power grid, and bring the needed confidence to grid operators: that PV capacity can be predictably ascertained on a day-ahead market.

6. ACKNOWLEDGEMENTS

Thanks to Bartholomy Obadiah for providing the 2005 SMUD system load data.

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TABLE 1
Comparing after-the-fact and forecasted ELCC
As a function of grid penetration
In Sacramento and New York City using ideal load forecasts

	GRID PENETRATION				
	2.00%	***5.00%***	***10.00%***	***15.00%***	***20.00%***
SACRAMENTO					
After the fact	68%	66%	62%	57%	51%
1-day forecast	71%	68%	64%	59%	53%
2-day forecast	71%	69%	64%	59%	53%
NEW YORK					
After the fact	61%	56%	47%	39%	33%
1-day forecast	61%	57%	50%	42%	35%
2-day forecast	59%	55%	48%	41%	35%

TABLE 2
Comparing after-the-fact and forecasted solar load control parameter
As a function of grid penetration
In Sacramento and New York City using ideal load forecasts

	GRID PENETRATION				
	2.00%	***5.00%***	***10.00%***	***15.00%***	***20.00%***
SACRAMENTO					
MWH needed without PV	127	830	4,989	17,416	41,417
fraction needed with PV (after the fact)	13%	8%	8%	8%	12%
fraction needed with PV (1-day forecast)	11%	6%	6%	7%	11%
fraction needed with PV (2-day forecast)	11%	6%	6%	7%	10%
NEW YORK					
MWH needed without PV	1,453	9,069	37,016	93,059	204,704
fraction needed with PV (after the fact)	6%	13%	23%	28%	30%
fraction needed with PV (1-day forecast)	6%	10%	22%	25%	26%
fraction needed with PV (2-day forecast)	7%	13%	23%	27%	28%

(note: the first row for each city represents the total amount of load management necessary without PV to accomplish peak load reduction amounting to the installed PV capacity, the % numbers in the other rows represent the fraction of the first row's amount that would be needed if PV was deployed – the lower the % value, the higher the capacity of PV.

TABLE 3
Comparing after-the-fact and forecasted ELCC
As a function of grid penetration
In New York City using operational load forecasts

	GRID PENETRATION				
	2.00%	***5.00%***	***10.00%***	***15.00%***	***20.00%***
NEW YORK					
After the fact	61%	56%	47%	39%	33%
1-day forecast	66%	62%	53%	44%	37%
2-day forecast	64%	61%	54%	46%	39%

TABLE 4
Comparing after-the-fact and forecasted solar load control parameter
As a function of grid penetration
In New York City using operational load forecasts

	GRID PENETRATION				
	2.00%	***5.00%***	***10.00%***	***15.00%***	***20.00%***
NEW YORK					
MWH needed without PV (actual load)	1,453	9,069	37,016	93,059	204,704
MWH needed without PV (forecasted load)	820	4,901	21,210	56,910	132,436
fraction needed with PV (after the fact)	6%	13%	23%	28%	30%
fraction needed with PV (1-day forecast)	9%	12%	13%	19%	21%
fraction needed with PV (2-day forecast)	12%	10%	14%	19%	20%