Solar Resource – Utility Load-Matching Assessment

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ABSTRACT

The principal objective of this study was to estimate the load matching capability of photovoltaics (PV) for a selected group of utilities in the continental United States. This report provides an initial quantitative estimate of this capability for twenty utilities.

This characteristic is important because it may indicate that the effective capacity, hence the value, of PV is higher than is traditionally assigned to such non-controllable, non-dispatchable resources.

Load matching capability is determined experimentally by analyzing the interaction between the load requirements of each utility and the output of locally-sited PV systems. This type of investigation requires site and time specific insolation data that are not commonly available. Here, the needed data was inferred from geostationary satellite remote sensing of the earth's cloud cover. A secondary objective of this study was to evaluate the suitability of this approach. The results of this investigation are presented in this report.

1. INTRODUCTION

1.1 Rationale

Our main goal is to provide a preliminary estimate of the match existing between the output of photovoltaic (PV) power plants operating within the service areas of US utilities and the load requirements of these utilities. For these utilities, many of which may yet be unfamiliar with their PV development potential, this information will indicate whether the effective capacity, hence the value, of this renewable resource should be higher than that assigned to a non-controllable, non-dispatchable resource.

While this investigation is currently limited to assessing utility-wide load-matching, it should be pointed out that a strong match at the utility-wide level will likely correspond to load matching occurrences at the transmission/distribution level for that utility, hence to possible high value T&D/DSM PV development opportunities [e.g., 1,2,3]. An absence of utility-wide match, on the other hand, should not preclude localized development opportunities.

1.2 Quantifying Load Matching

Actual, time-coincident utility load and PV output data covering a statistically significant period (at least one year) are necessary to characterize and quantify the relationship existing between the two quantities.

Hourly system load data are generally archived by utilities. However, actual PV output data are generally not available. Short of actual output data, it is possible to adequately simulate PV systems [4] if actual irradiance data are available. Unfortunately, with rare exceptions, that data are generally not available either. In this study, we circumvent the problem by using a proxy measurement of solar radiation with wide geographical coverage provided by geostationary satellites. These continuously monitor cloud cover over entire continents with a potential resolution of 2-3 miles at mid latitudes.

1.3 A Pilot Study Demonstrating the Approach

A pilot study undertaken on behalf of the New York Power Authority as part of an International Energy Agency task [5,6] demonstrated the validity of the satellite-based approach. For four utilities in southern New York State, the load matching capability of PVs estimated from satellite data was compared to that estimated from a Manhattan-based prototype system.

The study showed that satellite-predicted irradiance in the region of interest was climatologically sound and exhibited little bias. Short term prediction errors were found to be more pronounced, notably for the direct irradiance component. However, the study also indicated that to better this short term error at a given point, a ground-based measurement station would have to be located no further than 65 km. Finally, the pilot study showed that the satellite's "end-use accuracy", that is the satellite's ability to provide a utility with a sound estimate of PV's load matching capability, was adequate.

1.4 Structure of this Report

The present study was divided in two phases:

- (1) A preliminary phase with the objective of confirming the results of the pilot study, in terms of satellite physical and end-use accuracy, for other US climates and utilities;
- (2) A main phase with the objective of quantifying the effective capacity of PVs for up to twenty interested utilities in the continental United States, using a common set of load matching benchmarks.

The report is structured along these two phases, with sections 2 and 3 relating respectively the findings of the first and second phase.

2. EVALUATION OF SATELLITE RESOURCE PHYSICAL AND END-USE ACCURACY

The objective of this phase was to confirm one of the key conclusions of the New York pilot study, namely that satellite-derived insolation data are adequate to estimate the relationship between PV output and the load requirements of a given utility.

The results of this phase were detailed in a mid-term report [7] and in related article [8]. A copy of the article is provided in Appendix A. Its main points and findings are summarized below.

An important distinction was also made between climatological solar data and real solar data. Climatological data are site specific but need not be time specific. Those data are often sufficient for system design, and the US resource is adequately documented for most applications. Real data must specify insolation at an arbitrary site and at an arbitrary time (year, day, hour). Real data are not commonly available. The present load-matching investigation requires real data. Our evaluation focuses on that type of data.

Another important distinction was made between physical accuracy and end-use accuracy of satellite data. The former pertains to the difference between solar irradiance estimated from the satellite and ground-measured irradiance, while the latter pertains to the difference between PV-utility load-matching quantified from satellite data and from ground-based data.

2.1 Physical Accuracy

The satellite-estimated data were compared to that measured at 8 ground truth-sites, in addition to the Albany ground truth station already used in the pilot study. These sites are listed Table 1. They include most of the main US climatic environments.

Hourly satellite-derived global irradiance data were generated from the four-to-six daily estimates provided by NOAA-NESDIS [9,10], using the kt'-based time inter/extrapolation technique described in [5,11]. Hourly direct irradiance was modeled from global irradiance [11a]. Further, plane of array irradiance was modeled from global and direct [11b].

The satellite data set from NESDIS has a resolution of 1° latitude by 1° longitude, exclusive of points above or nearby large bodies of water. Therefore, for a given ground truth point, the corresponding satellite estimate were obtained via interpolation from the $1^{\circ} \times 1^{\circ}$ grid (*at the latitude of the US, this resolution amounts to about 70 by 45 miles.*) Further, for coastal ground truth sites, such as Cape Canaveral, FL, or San Jose, CA, the satellite estimates were obtained via extrapolation from inland grid points. (It should be noted that these limitations are not inherent to the satellite.)

Physical accuracy is quantified in terms of short term error (Root Mean Square Error -- RMSE) and long term bias (Mean Bias Error -- MBE) [6, 11b].

Two points of references may be used to put the satellite's physical accuracy in a practical perspective and judge of the method's overall merits and suitability for this study.

The first point of reference is specific to this study and consists of the accuracy observed in Albany, New York. We recall that the level RMSE found in Albany was found to be acceptable for an adequate determination of PV load matching capability of locally sited utilities [5].

In Fig. 1 the hourly satellite-predicted global irradiance has been plotted against ground truth irradiance for the nine considered sites. This figure indicates a reasonable agreement between ground and satellite and suggests the following comments:

- (1) The worse agreement between ground and satellite, as estimated from data scatter, is found in Albany, particularly with respect to the western sites. One reason may be the higher incidence of inhomogeneous cloud cover conditions in the northeastern region..
- (2) The well defined lines of points below the one-to-one line, observed in Waseca, Lamberton, and to a smaller extent in Albany NY, are very likely caused by winter time ground snow cover that is identified by the satellite as cloud cover. However the implications of this should be minimal for this study as discussed below.

The results displayed in Fig. 1 are summarized and quantified in Table 1. Mean bias errors are reasonable for all sites and range, in relative terms, from -5% to +6%. RMSEs are noticeably larger, ranging in relative terms from 16% to 25%. The largest relative RMSE is found in Albany.

Results for direct and tilted direct irradiance are detailed in Appendix A. In brief, short term errors (RMSEs) for the direct component are found to be considerably larger, while long term errors (mean bias) remain reasonable. However errors for tilted irradiance are found to be only slightly larger than for the global component; this is because any error in direct tends to be compensated by an opposite error in the anisotropic diffuse component.

Figure 1: Satellite-predicted (Y-axis) vs. ground-measured hourly global irradiance (X-axis) for nine US locations

Table 1

**Root Mean Square and Mean Bias Error of
satellite-predicted global irradiance at nine reference locations.**

SITE	MBE (W/m^2)	RMSE (W/m^2)
Cape Canaveral (FL)	17 (4%)	115 (25%)
San Jose (CA)	19 (4%)	91 (19%)
Carissa Plains (CA)	-13 (-3%)	80 (16%)
Mesa (AZ)	-20 (-4%)	80 (15%)
Keystone (CA)	-4 (-1%)	69 (14%)
Albany (NY)	4 (1%)	102 (28%)
Waseca (MN)	-24 (-6%)	100 (27%)
Lamberton (MN)	-12 (-3%)	96 (26%)
Austin	30 (6%)	118 (25%)

The second point of reference is more general. It consists of the accuracy achievable at a given point from a nearby ground measurement station. A considerable amount of work was accomplished in this area within the context Task 9D of the International Energy Agency's Solar Heating and Cooling Program (IEA-SHCP) [6], in which the author took part. A critical finding of this study is summarized in Fig. 2: the error made when

extrapolating global irradiance from a given ground station has been plotted against the distance from that ground station. This experimental evidence is based on daily global irradiance data collected in 6 measurement networks in Europe and North America. The following comments are warranted:

- (1) The error trend exhibits little site-climate dependency, hence appears to be "quasi-universal" for mid-latitudes.
- (2) Beyond a threshold of the order of 50-80 km (30-60 miles) from a measuring station, the satellite (with 16-25% RMSE) becomes the most accurate option. Furthermore, this break-even distance may be conservative with respect to the satellite for two reasons: (i) the extrapolation trend from ground point is based on daily totals and is likely to be considerably more pronounced at the hourly level. (ii) we relied on the simple (yet effective) NOAA-NESDIS satellite algorithm, as well as on time/space interpolation/extrapolation from a large grid which may not represent the ultimate capability of the satellite.

Figure 2: Extrapolation root mean square error as a function of distance from measuring station (from [6]), based on data from six networks in Europe and the US.

2.2 End-Use Accuracy

End use accuracy was assessed by comparing utility load-matching benchmarks determined from the satellite data with benchmarks determined from the ground measurements. (Load matching benchmarks are defined and discussed in section 3.1.1 below.)

This exercise was accomplished for three of the participating utilities (see list in section 3.2) where corresponding ground truth data were also available: Florida Power and Light, Salt River Project and Pacific Gas & Electric. For these utilities the agreement between ground and satellite for two critical benchmarks was found to be quite reasonable: the effective load carrying capability derived from the satellite was found to differ by no more than 6% from that derived from ground data. (see section 3 and Figs. 4-5 in Appendix A). These findings confirm the results of the New York pilot study for three other key US climatic environments.

3. QUANTIFYING LOAD MATCHING FOR 20 US UTILITIES

3.1 Methods

3.1.1 Benchmarking Load Matching

We use four complementary benchmarks to quantify the load matching capability of PV. These include:

- The Effective Load Carrying Capability (ELCC)
- The Normalized Energy Worth (NEW)
- The Mean Output during Highest hourly Loads (MOHL)
- The Minimum Buffer Energy Storage (MBES)

Each benchmark is determined from hourly PV output and utility load data.

ELCC: This statistical measure of effective capacity was introduced by Garver [12] who defined it as the effective increase in a utility's installed capacity due to the added resource, at constant loss of load probability (LOLP). Here, in order to compare results between utilities, we use a normalized version of the ELCC that assumes a generic LOLP for all utilities. Hence, this normalized benchmark is only a function of the resource/load relationship and of the penetration of PV on the considered grid. We consider PV penetration levels ranging from 2% to 20% of observed peak loads.

NEW: This parameter was originally used by Hoff [13] for a PG&E study. It is defined as the mean value of PV-generated energy using a normalized energy rate scale based on each utility's load duration curve. The curve is divided in ten intervals along the time axis. Each interval corresponds to an energy rate ranging linearly from 0.05 (lowest loads) to 0.95 (highest loads).

MOHL: This is defined as the mean PV output during the "n" highest observed hourly loads on the considered grid. Here, the MOHL is calculated for cumulative values of n equal to 10, 25, 50, 250, 500, 1000 and 2500.

MBES: The first three benchmarks represent statistical/stochastic measures of load matching. This is not the case for the MBES which is a bottom line/ worse case measure of load matching. We calculate the minimum amount of ideal energy storage necessary over the entire considered period, to guarantee that a PV+storage system will result in a firm peak load reduction equal to a fraction, F, of PV's installed capacity. Here we consider firm peak load reductions ranging from 1% to 20% with F ranging from 100% down to 60%. For each level of peak load reduction, we compare the MBES to the total energy storage, TES, that would be necessary to achieve the same reduction in the absence of the resource.

(Note that, in a utility growth context, the MBES benchmark may also be defined as the minimum storage necessary to guarantee that the PV+storage system will result in a firm increase in installed capacity.)

3.1.2 Time Period of Load Matching Study

The load matching study spans the years 1987 and 1988. These two years were selected for practical reasons: they represent a compromise between affordability, data quality, and actuality. In terms of affordability, the GOES satellite data used to simulate PV output throughout the USA were routinely pre-processed by NOAA-NESDIS since the early 1980s as part of a USDA program, and made available to this project [10]. In terms of quality, we were notified that, because of aging and lack of replacement, the satellite's data quality had been deteriorating since the late 1980s [10]. In terms of actuality we were interested in the most recent data, since utility loads do evolve over time.

The climatological representativeness of 1987 and 1988 in terms of solar resource will be formally investigated as part of the next phase of this program. However, the relevance of this matter to this study's conclusion is discussed below. Figure 3 shows the mean distribution of satellite-estimated global and normal incidence direct irradiance over the US for the considered 1987-88 period. Note that the general features of these maps are slightly different from the original irradiance maps provided until now by the USDOE, with relatively more resource in the east and less in the west. The newly released 30-year NREL Solar Radiation Data Base [14] exhibits a comparable departure from the original maps. Also note that key solar microclimates are adequately delineated: for instance, the Rocky Mountains and Appalachian piedmont areas, or the arid area in the wake of the Cascades are zones of solar radiation enhancement as would be expected.

3.1.3 Simulating PV Output

Hourly PV output is simulated using the program PVFORM 3.3 [15]. This program was recently evaluated against field data [4] and was found to adequately model the output of mainstream flat-plate crystalline silicon-based PV systems. The original code of PVFORM was modified to simulate PV output using standard time as a reference rather than solar time, so as to be in synchronicity with the utility load data.

Two array configurations were considered for each simulation: (1) fixed tilt at site latitude; and (2) two-axis tracking. (The results for one-axis systems should be intermediate between these two extreme configurations). The considered PV systems are rated in terms of summer AC output, whereby nominal AC output is achieved under 1000 W/m² plane of array insolation and a module temperature of 46 °C (PVFORM's default reference temperature). In addition, we assumed a 20% oversized power conditioning unit (PCU) for each simulation; hence PV output may exceed rated output for high insolation and/or cold weather conditions.

The input to PVFORM consists of hourly global and direct irradiance data plus hourly wind speed and temperature data. Wind and temperature data were obtained from the National Climatic Data Center [16] for locations within and/or nearby considered utility service areas. Global and direct irradiance data are extrapolated from the GOES satellite images as explained above. The limitations of this data set, which, again, are not reflective of the satellite's ultimate capability, are briefly reminded below.

- Hourly data are time extrapolated from 4-6 daily instantaneous images, with direct modeled from global.
- Data are available on a 1°X1° latitude/longitude grid
- Each grid point is an integration of several satellite pixels, representing a 2,500 km² ground foot print. Hence, each simulated PV output represents an ensemble of PV systems distributed over this area.
- Data were not processed by NESDIS for grid points over large bodies of water. Therefore, many coastal grid points are missing. As a consequence, PV output for coastal utilities had to be extrapolated from the closest inland grid-points (the effects of coastal extrapolation on data accuracy were physically quantified in Section 2, comparing satellite with the coastal ground truth stations of Cape Canaveral and San Jose). The maps in Fig. 3 show the available satellite grid points superimposed on the coastlines of North America.
- Data were missing for the last four months of 1988 for the continent's western half (this should not have a major impact on this study since the load matching capability of PV is mostly a function of their summer output).

For a given utility, the PV output considered in this study is that of systems dispersed over its entire service area. For service areas spanning several grid points, the considered output is the average of all grid points in the service area. For smaller service area, the considered PV output is a distance-weighted average between that of neighboring grid points. (Note that any PV distribution scenario could be selected from the present satellite data base, including, for instance, PV systems concentrated around metro areas, or systems located outside a service area).

Global Irradiance 1987/8 (wh/sq.m/day)

Direct Irradiance 1987/8 (wh/sq.m/day)

Figure 3: Average 1987-88 daily global and direct irradiance in North America estimated from satellite

3.2 Selected Utilities

Most of the utilities presently investigated elected to take part in this study and provide us with 1987-88 system load data, after having been contacted by the project managing team at NREL or by the author. Some utilities were also included because their load data had been made available to us by the New York Power Authority as part of the pilot study mentioned earlier [5]. The participating utilities are listed below.

1.	Atlantic Electric	(AE)
2.	City of Austin Power & Light	(APU)
3.	Consolidated Edison	(CONED)
4.	Delmarva Power	(DELMARVA)
5.	Florida Power and Light	(FPL)
6.	Gainesville Regional Utilities	(GRU)
7.	Idaho Power Corporation	(IPC)
8.	Kansas City Power and Light	(KCPL)
9.	Lincoln Electric System	(LES)
10.	Long Island Lighting Company	(LILCO)
11.	New York Power Authority (South NY Sector)	(NYPA)
12.	Niagara Mohawk Power Corporation	(NMPC)
13.	Northern State Power	(NSP)
14.	Omaha Public Power District	(OPPD)
15.	Pacific Gas & Electric Company	(PGE)
16.	Public Service Company of Colorado	(CPSC)
17.	Salt River Project	(SRP)
18.	Southern Electric System	(SES)
19.	St. Joseph Light & Power Company	(SJPL)
20.	Wisconsin Public Service Corporation	(WPS)

Figure 4: Service areas of the considered utilities (note: the gray scale used to fill service areas corresponds to the observed level of PV load matching)

Each utility's service area has been reported in Fig. 4. As can be seen, the present utility sample is well balanced geographically and includes most major US regions, with the exception of the Pacific Northwest. Service areas range in size from a few km² (GRU, APU, LES) to over 100,000 km² (e.g., PGE, NSP).

Loads: The present utility sample is also quite diverse in terms of peak loads that span two orders of magnitude from 100's of MW to 10's of GW.

The observed summer and winter peak loads of each utility have been plotted in Fig. 5. Summer and winter mean loads are shown in Fig. 6. The ratio summer-to-winter mean loads and summer-to-winter peak loads are plotted in Fig. 7. All but one utility were summer peaking in 1987-88, both in terms of mean load (i.e., energy) and peak load (i.e., capacity); however, the hierarchy among utilities is markedly different for energy and capacity ratios. For instance, FPL's summer-to-winter energy ratio is one of the highest, but its capacity ratio is only slightly summer-peaking (this can be qualitatively interpreted by the fact that despite a much broader energy demand from air conditioners in summer, a few winter cold snaps associated with electric heating may drive winter loads to high levels.) On the other hand, NSP, which is marginally summer-peaking in terms of energy, features a much higher capacity ratio (likely because of the impact of a few strong heartland summer heat waves on air conditioning).

PV Resource: The mean summer and winter PV resource of each utility is compared in Fig. 8. This resource is illustrated here by the mean hourly output of a nominal 1-kW two-axis PV capacity dispersed over each considered service area. Summer output is defined in this illustration, as the mean output for June-August, while winter output corresponds to December-February. It is noteworthy to remark that differences in summer production throughout the US are not considerable. On the other hand, differences are much more pronounced in winter, and the hierarchy among locations is markedly different: two extreme examples are Florida Power and Light, with one of the highest winter resource, but one of the lowest in summer, and Idaho Power Corporation, with one of the highest summer resource, but a relatively low winter resource. (These two examples are consistent with known climatological and geographical -- latitude -- characteristics of the considered sites). Finally, it is important to recall that the winter resource observed for some of the northernmost locations may be artificially low, because ground snow-cover may be mistakenly identified by the

Figure 5: Summer and Winter Peak loads (MW) for the 20 selected utilities

Figure 6: Summer and Winter Mean loads (GW) for the 20 selected utilities

Figure 7: Ratio of summer-to-winter peak loads and summer-to-winter mean loads for the selected utilities.

satellite as cloud cover (see Fig. 1 and section 2.1) the overall impact of this should be limited, however, both in physical terms, as well as in end-use terms, because the critical period for PV load matching is summer.

3.3 Load Matching Results

3.3.1 Qualitative Overview: Mean PV Output vs. Seasonal Load Requirements.

Before presenting the load matching results per se, it is useful to qualitatively assess the correspondence between each utility's load and its PV resource. This is done in a series of graphical summaries that compare summer, winter, peak and mean daily system load profiles to the mean winter and summer output of fixed and tracking 1-kW PV systems. A total of 40 such graphical summaries have been generated, corresponding to each utility and each year studied. A sample graphic summary is provided in Fig. 9 (LILCO, 1987): summer mean and peak daily load profiles are represented on the top left chart; winter loads are shown on the top right chart; summer PV output is shown on the bottom left for fixed and two-axis tracking systems, while winter PV output is shown on the bottom right.

Figure 8: Mean hourly PV output per kW of installed capacity dispersed on each service area in summer and in winter. (This assumes summer conditions AC-rating and 2-axis tracking arrays).

We briefly comment here on the case of four utilities with distinctive features that may be useful for understanding and interpreting the load matching results presented below. These utilities are CONED, KCPL, SRP and FPL . Graphical load-resource summaries are provided in Appendix B for these four utilities.

CONED: This utility serves the large metropolitan customer base of New York City. Its summer load exhibits a marked "9-to-5" pattern due to commercial demand and a strong mean-to-peak excursion in summer, likely caused by increased air conditioning usage during heat waves ("heat wave effect"). The summer PV output is well in phase with the load. The winter load is notably lower and appears more stable, as indicated by a limited mean-to-peak span.

KCPL: Typical of several mid-size midwestern metropolitan utilities studied here, KCPL exhibits a strong summer-to-winter peak load ratio, as well as a strong summer mean-to-peak excursion (heat wave effect). The daily peak extends later in the day than ConEdison's but, is still well in phase with PV output. The winter load is very stable, both in terms of daily excursion and mean-to-peak excursion.

SRP: This utility is characterized by one of the highest PV resource in the US. However, its summer peak occurs in the evening, out of phase with PV output. (This is likely due to a large residential air conditioning base). The mean-to-peak summer load excursion is much smaller than for the two

previous utilities. However, the winter mean-to-peak excursion is larger and leads to a noticeable morning winter peak (a likely result of the reaction of this utility's electric heating base to cold snaps).

FPL: Although FPL's summer peak occurs slightly earlier in the day than SRP's, it is still noticeably out of phase with PV output; in addition, summer PV output tends to degrade in the afternoon (likely because of the high occurrence of thunderstorms.) The electric heat-based winter peak effect mentioned for SRP is considerably more pronounced here, as this utility reacts to cold snaps with a marked early morning peak. The summer load profile, on the other hand, is quite stable in terms of mean-to-peak span, unlike that of KCPL and CONED that exhibit strong reactions to heat waves.

A general observation for all utilities: winter peaks are substantially narrower than summer peaks, even for the one winter-peaking utility considered here. The implications of this on load matching are discussed below.

Figure 9: Sample load-resource graphical summary

3.3.2 Presentation of utility-specific load matching results

Load matching results obtained for each of the four benchmarks are reported in a standard forms. A total of 80 such forms were produced corresponding to each utility, each year studied and each PV configuration. In order to facilitate the review of these results, the contents of each forms are graphically summarized. Forms and graphics are provided in Appendix B for the four utilities discussed above. A sample graphical summary is shown in Fig. 10. Each graphic summary contains four charts corresponding to each benchmark:

- The relative ELCC (%) is plotted as a function of grid penetration in the top left chart. Note the gradual decrease of ELCC with PV penetration.
- The histogram in the bottom left chart illustrates the distribution of total PV energy as a function of a five-bin normalized rate scale based on each utility's load duration curve. For all considered utilities, this distribution is strongly skewed toward the high rate bins.

- The top-right chart compares MBES requirements to storage needs without PV for five levels of peak load reduction. This chart corresponds to a PV fraction $F = 100\%$; that is, the peak load reduction goal is equal to the installed PV capacity.
- Finally the bottom right chart shows the distribution of mean PV output as a function of the number of considered highest loads.

Figure 10: Sample load matching graphical summary

3.3.3 Synthesis of Results and Discussion

We attempt here to summarize the load matching results from all utilities studied into a compact fashion that is helpful to discern general trends.

We make extensive use of the utility summer to winter peak load ratio (**SWP ratio**), as a background against which display result summaries. The SWP ratio was selected because of the strong relationship observed between this ratio and experimentally derived load matching parameters; (other utility-characterizing variables available to us were not found to exhibit such a strong relationship).

The Four Benchmarks

ELCC: The relative ELCC of two-axis tracking PV systems is plotted in Fig. 11 as a function of the SWP ratio for utility grid penetration levels of 2%, 10% and 20%. Each point represents a mean for 1987 and 1988 values.

The quasi-logarithmic growth of PV's ELCC as a function of the SWP ratio is remarkable: All the utilities studied, from winter-peaking to highly summer peaking, fit the pattern, a priori regardless of their size or other characteristics. Further, some of the scatter around the trend may be traceable to other load shape factors; for instance, points above the trend tend to correspond to utilities peaking earlier in the day in summer (e.g., DELMARVA) than points below the trend (e.g., SRP, AE).

The ELCC reaches remarkably high values for several utilities, especially at low penetration levels. (Note that the ELCC of fixed systems is about 15-20% less than that of tracking systems). PV's ELCC is found to decrease as utility penetration increases, this effect being most pronounced for utilities with low summer to winter peak load ratios. Indeed, as PV penetration increases, the resource must meet non-summer day time loads to maintain a high ELCC; these loads may not be correlated with the resource; hence, the higher the SWP ratio, the more PV a utility can absorb and still focus on addressing its summer day time peak load with PV.

NEW: The mean 1987-1988 PV Normalized Energy Worth derived for each utility is plotted in Fig. 12 against the SWP ratio. This benchmark is fairly high for all utilities and only a weak trend is noticeable as a function of the SWP ratio: this is likely a consequence of the fact that the loads of all utilities considered here are sun-synchronous, with broad day time ridges and broad night-time valleys in all seasons.

Figure 11: Relative ELCC vs. SWP load ratio at 2%, 10% and 20% PV penetration (2-axis trk.)

Figure 12: Normalized Energy Worth (NEW) vs. SWP ratio

The NEW benchmark is not very discriminatory, however it does reflect the fact that the energy value of PV is higher than average, even for the only winter peaking utility considered here (in support of this assertion, note that time-of-day energy retail rates presently in effect for NMPC [17] also yield a higher than average energy value for PV).

MOHL: The Mean PV Output during the Highest 50, 250 and 1000 highest Loads of the twenty utilities is graphically presented in Fig. 13 as a function of the SWP ratio. The MOHL benchmark is found to be remarkably high for several of the utilities. Trends are similar to that of ELCC, but these are less marked and exhibit more scatter, especially when only the top 50 loads are

considered; in this case, the observed scatter for a given SWP ratio may be attributed to both local short term weather variability at peak time, and to the time of the peak load -- utilities below the trend include FPL, SRP and GRU, peaking late in the day in summer and prone to experience late afternoon weather deterioration. When a large number of loads are considered, the relationship between MOHL and the SWP becomes less marked. This is because the MOHL benchmark becomes ultimately equal to the resource's Capacity Factor when all loads are considered and, at that stage, is no longer a function of the considered utility, but depends solely on the solar resource.

MBES: In Fig. 14 the Minimum Buffer Energy Storage to guarantee a firm 10% peak load reduction is compared to the total energy storage (TES) that would be required to accomplish the same reduction without PV. The storage unit is system-hours, with system size at 10% of each utility's peak load. The TES is mainly a function of the broadness/flatness of the utility's daily peak. The use of the PV resource considerably reduces energy storage requirements in all cases, including winter peaking NMPC (for this utility, as for most other utilities considered here, winter peaks are narrower than summer peaks, hence may be met with less storage, even if they are higher). The ratio between MBES and TES decreases with the SWP ratio following a trend similar to that of the other benchmarks (see Fig. 15).

Figure 13: Mean PV Output during the Highest 50, 250 and 1000 Loads (MOHL) vs. the utility SWP ratio

Figure 14: Minimum Buffer Energy Storage (MBES) required to guarantee a firm 10% peak load reduction with PV, compared to Total Energy Storage (TES) required to achieve a similar reduction without PV

Figure 15: MBES-to-TES ratio versus utility SWP ratio to guarantee 20% firm peak load reduction.

Bottom Line

Composite Benchmark: The results may be further summarized in order to provide a quick "bottom-line" overview of load matching capability. For this purpose, we arbitrarily defined a composite benchmark, function of the four others. At a given grid penetration level v , the composite benchmark, CB is given by:

$$CB = 0.25 \times [ELCC_v + NEW + MOHL_{n(v)} + (1 - MBES_v/TES_v)], \quad \text{with } n(v) = v \times 8760 \text{ hr.}$$

Results for this composite benchmark are presented in Fig. 16.

Fixed vs. Tracking PV: The load-matching performance of fixed systems in relation to two-axis tracking systems may be gauged in Fig. 16. On average, the non-tracking option will result in a 10-15% reduction of load matching capability. Differences may be traced to the hour of the summer peak: for utilities such as CPSC and CONED whose loads peak early in the day, the performance of fixed systems approach that of tracking systems.

Conversely, for late peakers such as SRP, AE or LES, the difference between the two array configurations is more pronounced.

Figure 16: Composite load matching benchmark (fixed vs. 2-axis tracking systems) estimated at 10% PV penetration for the 20 selected utilities.

Geographical Distribution: The gray scale used to fill the service area of each utility on the map in Fig. 4 relates to their load matching capability as summarized in Fig. 16. Based on the limited evidence gathered here, zones of highest load matching capability include the southwestern seaboard (a well documented fact [e.g., 2]), the heartland (from Texas to Minnesota), and to a lesser extent, the eastern sea board; by contrast, two areas traditionally considered as prime for solar development, the Florida peninsula and the southwest arid lands, do not fare as well on the load matching scale.

Solar Energy Resource vs. Load Matching: Comparing the solar resource map in Fig. 3 and the load matching map in Fig. 4, it is apparent that the distribution of the resource and PV load matching capability are not strongly related: provided that the summer solar resource is reasonable (as is the case for all regions studied),

Figure 17: Composite load matching benchmarks (two-axis tracking) estimated at 10% PV penetration versus mean summer PV output.

opportunities for load matching are not a function of the resource's magnitude, but of the load requirements in relation to the resource. This small degree of dependence on the resource may be further ascertained in Fig. 17, where the composite load matching benchmark at 10% penetration has been plotted against the mean summer output of fixed tilt PV systems.

This observation should not be interpreted as a statement that the solar resource is not an important parameter. The resource is critical, but less in terms of its overall

magnitude than in terms of its feed-back relationship with load requirements: if solar energy indirectly drives the load, the overall magnitude of the resource should not be of prime relevance.

Representativeness of the 1987-88 period:

The climatological representativeness of the selected years will be formally investigated as part of a following phase to this study.

However, based on the argument developed above, this question should not be critical.

For now, comparing the load matching benchmarks derived for 1987 and 1988 (Fig. 18), it

is apparent that the results are stable from one year to the next (less than 5% variation for most utilities), increasingly with the utility SWP ratio. This would indicate the presence of a robust relationship between the solar resource and the load requirements.

Figure 18: Relative difference between load matching benchmarks derived from 1987 and 1988 data

4. CONCLUSIONS

The main objective of this study was to estimate the load matching capability of PVs for a selected group of utilities in the continental United States.

To accomplish this objective it was necessary to access short time step insolation data at arbitrary locations and times in the country. Geostationary satellites have the potential to provide the needed data. Hence a secondary objective was set to evaluate the accuracy of satellite-derived insolation data for the purposes of estimating PV-utility load matching. The results of a comparison with nine ground truth stations representative of distinct US climatic environments are consistent with that of our pilot study confined to the northeastern US [5]. It is reasonable to conclude that satellite derived insolation may be used to provide an initial estimate of PV's load matching potential for American utilities. This study further points out that (1) satellite data constitute the most accurate option beyond 35-50 miles of a ground-based measuring station and (2) currently operational satellite-to-irradiance procedures provide a conservative assessment of the ultimate potential of satellite-aided solar resource monitoring.

Concerning this study's primary objective, our main observation and conclusions are the following:

- The load matching capability of PV, as quantified with four independent benchmarks was found to be substantial for many of the twenty considered utilities. Thus, a PV-based resource, either on the demand or the supply side, could effectively contribute to meet these utilities' capacity requirements. We note that load matching capability decreases with the level of PV penetration; however, in the best cases, PV retains a strong effective capacity at penetration levels of 20%. We finally note that the effective capacity of tracking systems exceeds that of south facing fixed systems by 5-15%.
- A well defined relationship was observed between a utility's summer-to-winter peak load ratio (SWP ratio) and the load matching capability of PV for that utility. The SWP vs. load matching trend was

observed independently of additional characteristics that may have been deemed important a priori, such as the considered utility's size (that spans several orders of magnitude here), its generation or customer mix, and even its overall solar energy resource.

We must caution, for now, that this observation is based on a limited 20-point data set. However should this trend be confirmed (and refined/qualified), its implications may be very useful for utility planners, particularly if it is found to persist at the sub-utility (T&D) level: knowing a utility's or sub-utility's SWP ratio would be sufficient to determine the corresponding PV capacity value. (Note that the smaller utilities considered here, correspond in size to sub-utility components of the larger ones).

- With the exception of California, most of the best PV load matching opportunities were found for locations not traditionally targeted for solar energy development, namely: the central US and the Mid-Atlantic seaboard. By contrast, the load matching potential of traditional solar energy regions (Florida, Arizona), was found to be more limited.

For many of the present utilities, these results constitute an initial screening of their utility-wide PV load matching potential. It is useful to repeat that a strong match will likely correspond to load matching occurrences at the transmission/distribution level, hence to possible high value PV development opportunities. An absence of utility-wide match, on the other hand, should not preclude localized development opportunities.

This initial estimation should be complemented with local R&D investigations.

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**SOLAR RESOURCE
UTILITY LOAD MATCHING ASSESSMENT**

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APPENDIX A

**EVALUATION OF SATELLITE DATA ACCURACY
FOR LOAD MATCHING CALCULATIONS**

Using Satellite-Derived Insolation for Real Time Simulation of Solar Systems

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We report on the accuracy of remote sensing from geostationary satellites for the purpose of simulating solar systems at the earth's surface and their interaction with electric utilities in North America. We focus our attention both on the physical accuracy of satellite-estimated insolation (global, direct, tilted irradiance) and on its "end-use" accuracy defined as the precision achieved on the end-product of the simulation.

1. INTRODUCTION

1.1 Climatological vs. Real Data: When evaluating the usefulness of satellite remote sensing to estimate solar irradiance at the earth surface, it is important to define the type of data one needs. Here, we distinguish between (1) climatological data and (2) real data. Climatological data are site-specific but need not be time-specific: Typical Meteorological Year data sets are examples of such data. Real data are both site and time specific: the time, day and year of each data point must be known: real-time data are an extreme example of real data.

Climatological data are often sufficient to design systems for a given site but not to investigate the interaction between these systems and their intended utilization, if there exists an undetermined relationship between the two: this is the case for solar systems (e.g., photovoltaics, Pvs) vs. the needs of some electric utilities [1,2]. If a positive relationship exists, Pvs may be used in high value peak load reduction applications [3]. However, real insolation data are necessary to characterize and quantify this potential. Here, we show that satellites are a sensible option to obtain usable real data in the absence of very dense ground measurement networks.

1.2 Physical vs. End-Use Accuracy: We make a distinction between the physical accuracy of insolation estimates and their end-use accuracy for a specific task. (1) The physical accuracy is the actual difference between estimated and measured insolation and is benchmarked in terms of mean bias (long term) error (MBE) and root mean square (short term) errors (RMSE). The latter is primarily relevant to real data. (2) End-use accuracy is task-dependent and is assessed in terms of the error performed on the end-product of the data analysis. In this paper, the end product load matching capability of PV generation for a given utility. We show that satellite-derived

data may be used effectively to this end in climatic environments similar to those found in Mexico.

2. PHYSICAL ACCURACY

2.1 Satellite vs. extrapolation from ground measurements: When no insolation data exist for a given site, a common palliative has been to use data from another point, or set of points, where data are available. This approach may be warranted when climatological data are needed, as long as (micro)climatic/environmental differences are small. This is much less true for real data because the time element becomes crucial.

A study recently undertaken [4] under the auspices of the International Energy Agency (IEA) dealt specifically with the issue of global irradiance network interpolation/extrapolation. One of its most interesting findings is reported in Fig. 1, where a clearly defined relationship has been established between the extrapolation distance and the resulting RMSE: this increases with the square root of the distance and reaches 20% at 50 km, confirming limited earlier observations by [5]. This trend appears to be universal since it is derived from over 70 measuring station-years in six climatically diverse networks in Switzerland, Germany, Sweden and the northeastern, northwestern and southwestern United States. A similar, although not as readily quantifiable trend, was found in the case of interpolation between stations, with a perceptible but small RMSE reduction when using sophisticated interpolation methods such as kriging [4].

By contrast, the study found that the RMSE of satellite-derived daily global irradiance was of the order of 17-22% for a large number of test sites in Europe, and the US — with a perceptible but overall small dependence on the location, the satellite and on the sophistication of the algorithm [4]. Hence,

for real data, satellite-derived insolation becomes preferable to ground extrapolation if distance exceeds 40-50 km.

These results are limited to daily global irradiance. Extrapolation errors are likely to be higher for hourly values since the cause of error, cloud cover inhomogeneities, would no longer be averaged. For satellite data, a limited study the for the northeastern US [6] showed only a small RMSE increase from a daily to an hourly basis. In this case, the cause of error (determination of turbidity and cloud thickness) is fundamentally different from that of extrapolation and is less affected by the time scale.

2.2 Physical validation of satellite-estimated hourly global direct and tilted irradiance for North American sites: We compare satellite-estimated hourly global irradiance against ground-measurements at six climatically distinct sites in the US. We also evaluate the accuracy of satellite-derived hourly direct irradiance and simulated PV output. The test sites are Cape Canaveral, FL (subtropical, humid), Albany, NY (continental, humid), Mesa, AZ, and Carissa Plains, CA (arid), Keystone, CA (semi-arid, mountains) and San Jose, CA (semi-arid/oceanic).

For the satellite we rely on five-to-six global irradiance estimates per day on a 1x1 degree latitude-longitude grid, based on the Justus Tarpley algorithm [7]. Each point is an integrated value of 25 pixels and represents a ground "foot-print" of about 2,500 km². Hourly data are time-extrapolated from these points as explained in [6] and estimates

at a specific location are interpolated from the grid (extrapolated for coastal sites, since the Justus-Tarpley method is not used over-water). Satellite direct irradiance is further modeled from global from [8]. Finally, PV output for a tilted collector is modeled using PVFORM [9]. (Note that ground-reference PV output is also modeled).

It is important to remark that this assessment of satellite accuracy is very conservative and could be improved in the future because: (1) we use the simplest, yet effective, satellite algorithm (the only routinely exploited for America), (2) we rely on time/space inter/extrapolation, (3) we model direct, amplifying any error in its global input.

The results are presented in Figs. 2, 3 and 4, where satellite estimates are plotted against ground values for global, direct and tilted PV output, respectively. They are consistent with the IEA findings for global irradiance: negligible MBE ($\pm 5\%$ range); RMSE ranging from 16% in California to 26% in New York. The scatter is considerably stronger for direct irradiance: while MBEs remain reasonable ($\pm 10\%$), RMSEs are in the 30-50% range. Interestingly, the simulated tilted PV output is little affected by the noise in the direct component: the MBE and RMSE of simulated PV are comparable to that of global irradiance (this is because for south facing collectors, any error on the direct tends to be compensated by an opposite error in the anisotropic diffuse component).

Figure 1: Relative RMSE (%) of extrapolation, as a function of distance from measuring station. Results based on data from 6 irradiance networks: USNEU (northeastern US), SMHI (Sweden), USWN (southwestern US), DWD (Germany), USPNW (northwestern US) and ANETZ (Switzerland)

Figure 2: Satellite-derived hourly global irradiance (Y) vs. ground measurements (X) at six reference sites

Figure 3: Satellite-derived hourly direct irradiance (Y) vs. ground measurements (X) at six reference sites

Figure 4: Satellite-derived hourly PV output on a fixed-tilt (Y) vs. ground-modeled output (X) at five reference sites

3. EFFECTIVE "END-USE" ACCURACY OF SATELLITE-DERIVED INSOLATION FOR INVESTIGATING PHOTOVOLTAIC INTERACTION WITH ELECTRIC UTILITIES

There are several benchmarks that can be used to quantify the peak load matching capability of non-dispatchable generating sources (e.g., [1,2]). These benchmarks may be derived from the analysis of time-coincident utility load data and power plant output data. Here, we focus our attention on two critical benchmarks. The first benchmark is statistical, while the second represents an absolute worse case measure of the resource's ability to meet demand.

1. The resource's effective load carrying capability (ELCC) defined as the effective increase in the utility's available capacity due to the added resource. If the resource is able to meet all the utility's high loads its ELCC will approach 100%.
2. The minimum buffer energy storage (MBES), needed to guaranty that the resource will meet all loads above a given threshold. The MBES is estimated in relation to the total energy storage (TES) needed to meet the same goal in the absence of the resource. For an ideally peaking resource, MBES = 0. For a resource with no load matching potential, MBES = TES.

A preliminary study in New York [6] concluded that the error between satellite and ground-derived benchmarks was not considerable and that satellite data could be used effectively for this type of investigation. Here, we extend this investigation

to other climates and utilities, including Florida (Florida Power and Light — FPL), Arizona (Salt River Project — SRP) and California, (Pacific Gas and Electric — PG&E). In each case results are based on two years (1987-88) of ground insolation and satellite data and utility hourly load data.

In Figure 5, we have plotted the variations of Pvs ELCC for each utility in relation to the resource's penetration on their grid, as derived from both ground insolation data and satellite data. Note that, in each case, notably PG&E, PV's ELCC is much higher than PV's capacity factor (of the order of 20-25%), indicating that PV can effectively contribute to meeting utility peak loads, particularly at low penetration levels. However, the point we want to stress here is the reasonably good agreement between satellite and ground derived ELCCs, which confirms and even strengthens the preliminary study's findings. In figure 6, we compare MBES and TES requirements for each utility, as estimated from ground and satellite data. Note that MBESs are considerably smaller than TESs, confirming the above benchmark even in the worse case situation. As above, we stress the remarkable agreement between satellite and ground derived MBESs (relatively to TESs).

4. CONCLUSIONS

This study confirms, on a multi-climatic North American scale, the key results of a localized preliminary study [6] making constructive use of the results of a comprehensive IEA task [4]. These results are: (1) the physical accuracy of satellite-

derived hourly global irradiance or fixed-tilt south facing irradiance is of the order of 20-25% RMSE and negligible MBE, making the satellite more suitable to real data acquisition than extrapolation beyond 50 km of a ground station. (2) Satellite-derived insolation is an effective means of assessing the potential of PV generation in relation to the needs of electric utilities for places with little access to ground data. Note that the climates investigated here are comparable to those found in large portions of Mexico: arid and semi-arid southwestern US, and humid subtropical southeastern US.

Finally, we stress again that this study is conservative with respect to the ultimate capabilities of the satellite. Three avenues for future improvement are: (1) higher resolution on-board sensors, (2) combination of satellite for spatial coverage and ground networks for real-time local satellite calibration and (3) stochastic and/or physical improvement of algorithms.

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Figure 5: Comparison between ground (-Gnd) and satellite-derived (-Sat) ELCC of PV power generation (2-axis tracking) for three US electric utilities as a function of PV grid penetration

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Figure 6: Comparison between ground and satellite-derived PV buffer energy storage (MBES) in relation to TES to guaranty a utility peak load reduction of 15%

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APPENDIX B

**EXAMPLE OF DETAILED RESULTS
FOR FOUR UTILITIES**

QUALITATIVE LOAD MATCHING ASSESSMENT

LOAD vs. RESOURCE

Illustrative examples for:

Consolidated Edison (1988)

Kansas City Power and Light (1988)

Salt River Project (1988)

Florida Power and light (1988)

CONED Summer Load; 1988

CONED Winter Load; 1988

CONED Summer Pv; 1988

CONED Winter Pv; 1988

KCPL Summer Load; 1988

KCPL Winter Load; 1988

KCPL Summer Pv; 1988

KCPL Winter Pv; 1988

SRP Summer Load; 1988

SRP Winter Load; 1988

SRP Summer Pv; 1988

SRP Winter Pv; 1988

FPL Summer Load; 1988

FPL Winter Load; 1988

FPL Summer Pv; 1988

FPL Winter Pv; 1988

QUANTITATIVE LOAD MATCHING ASSESSMENT LOAD MATCHING SUMMARY FORMS

Illustrative examples for:

Consolidated Edison (2-axis tracking, 1988)

Kansas City Power and Light (2-axis tracking, 1988)

Salt River Project (2-axis tracking, 1988)

Florida Power and light (2-axis tracking, 1988)

Description of Load Matching Summary Forms

<u>LCC %</u>	<u>LCC</u>	<u>%Max%</u>	<u>%MW</u>
38.55	12.2	2.00	32
37.40	17.7	3.00	47
22.98	69.0	19.00	300
22.34	70.6	20.00	316

ELCC Benchmark, including

relative ELCC (LCC%)

Actual ELCC in MW, (LCC)

Percent PV penetration on grid (%Max%)

Corresponding installed PV capacity (%MW)

<u>PPLR</u>	<u>Sx60</u>	<u>Sx70</u>	<u>Sx80</u>	<u>Sx90</u>	<u>Sx100</u>	<u>S'</u>
1.0	0.28	0.41	0.53	0.65	0.78	1.29
2.0	0.51	0.68	0.84	1.00	1.16	2.15
15.0	2.34	2.90	3.46	4.08	4.73	11.52
20.0	2.62	3.23	3.84	4.54	5.41	12.68

<u>Load</u>	<u>%PV</u>	<u>Weight</u>	<u>Cases</u>
100- 90	19.2	0.95	839
90- 80	13.3	0.85	839
20- 10	2.8	0.15	839
10- 0	1.5	0.05	846

MBES Benchmark, including

Percent peak load reduction (PPLR)

Minimum buffer storage required to

reduce load by F% of PV

installed capacity (SxF);

storage unit is system-hour.

TES, storage needs without PV (S')

Weighted Energy Worth: 65.094

Utility energy output (MWH): 9006031

Total PV: 1534057

Highest considered load: 1580 MW.

Highest overall load: 1580 MW.

Probability of Maximum Peak Reduction

10: 0.3748

25: 0.5896

| |

| |

2500: 0.2791

8397: 0.1827

NEW Benchmark, including

Considered load duration curve interval (Load)

Fraction (%) of total PV output corresponding to the considered interval (%PV)

Normalized energy worth on a

0-1 scale (Weight)

Number of considered hourly loads (Cases)

Normalized (weighted) Energy Worth (NEW)

on a 1-100% scale

MOHL Benchmark, Including

Number of considered highest loads (1st Col.)

Corresponding Mean PV availability, % nominal (2nd Col.)

LCC %	LCC	%Max%	%MW
79.01	138.7	2.00	176
78.42	206.5	3.00	263
77.79	273.1	4.00	351
77.12	338.4	5.00	439
76.42	402.4	6.00	527
75.67	464.9	7.00	614
74.88	525.7	8.00	702
74.05	584.9	9.00	790
73.18	642.2	10.00	878
72.27	697.6	11.00	965
71.31	751.0	12.00	1053
70.31	802.2	13.00	1141
69.28	851.2	14.00	1229
68.21	897.9	15.00	1316
67.11	942.3	16.00	1404
65.98	984.4	17.00	1492
64.83	1024.2	18.00	1580
63.66	1061.6	19.00	1667
62.48	1096.7	20.00	1755

PPLR	Sx60	Sx70	Sx80	Sx90	Sx100	S'
1.0	0.00	0.00	0.00	0.00	0.04	1.95
2.0	0.00	0.00	0.00	0.00	0.04	2.87
3.0	0.00	0.00	0.00	0.00	0.04	3.58
4.0	0.00	0.00	0.00	0.00	0.04	4.19
5.0	0.00	0.00	0.00	0.00	0.04	4.65
7.5	0.00	0.00	0.00	0.01	0.16	5.61
10.0	0.00	0.00	0.00	0.11	0.29	6.24
15.0	0.08	0.15	0.22	0.29	0.45	7.30
20.0	0.38	0.51	0.64	0.78	1.00	8.53

Load	%PV	Weight	Cases
100- 90	22.3	0.95	840
90- 80	14.9	0.85	840
80- 70	15.6	0.75	840
70- 60	13.3	0.65	840
60- 50	7.8	0.55	840
50- 40	8.1	0.45	840
40- 30	9.6	0.35	840
30- 20	6.0	0.25	840
20- 10	1.8	0.15	840
10- 0	0.6	0.05	848

Weighted Energy Worth: 67.305

Utility energy output (MWH): 35476143

Total PV: 2217036

Highest considered load: 8776 MW.

Highest overall load: 8776 MW.

Probability of Maximum Peak Reduction

10: 0.8884

25: 0.8611

50: 0.8686

250: 0.7686

500: 0.6617

1000: 0.5648

2500: 0.4651

8408: 0.2637

LCC %	LCC	%Max%	%MW
78.80	41.9	2.00	53
78.12	62.2	3.00	80
77.39	82.2	4.00	106
76.61	101.7	5.00	133
75.78	120.8	6.00	159
74.89	139.2	7.00	186
73.95	157.1	8.00	212
72.96	174.4	9.00	239
71.91	191.0	10.00	266
70.81	206.9	11.00	292
69.65	222.0	12.00	319
68.45	236.3	13.00	345
67.20	249.9	14.00	372
65.92	262.6	15.00	398
64.60	274.5	16.00	425
63.25	285.6	17.00	452
61.89	295.9	18.00	478
60.51	305.3	19.00	505
59.12	314.0	20.00	531

PPLR	Sx60	Sx70	Sx80	Sx90	Sx100	S'
1.0	0.00	0.00	0.00	0.03	0.13	1.95
2.0	0.00	0.00	0.00	0.03	0.13	2.63
3.0	0.00	0.00	0.00	0.03	0.13	3.28
4.0	0.00	0.00	0.00	0.03	0.17	3.71
5.0	0.00	0.00	0.00	0.03	0.20	3.97
7.5	0.00	0.00	0.00	0.05	0.24	4.55
10.0	0.00	0.00	0.00	0.06	0.31	5.16
15.0	0.39	0.48	0.57	0.66	0.92	6.71
20.0	0.71	0.85	0.99	1.19	1.61	8.03

Load	%PV	Weight	Cases
100- 90	21.8	0.95	839
90- 80	13.5	0.85	839
80- 70	12.1	0.75	839
70- 60	14.8	0.65	839
60- 50	13.1	0.55	839
50- 40	8.0	0.45	839
40- 30	6.3	0.35	839
30- 20	5.7	0.25	839
20- 10	3.9	0.15	839
10- 0	0.9	0.05	845

Weighted Energy Worth: 65.906

Utility energy output (MWH): 10468101

Total PV: 2461170

Highest considered load: 2656 MW.

Highest overall load: 2656 MW.

Probability of Maximum Peak Reduction

10: 0.9083

25: 0.8842

50: 0.8853

250: 0.7507

500: 0.6893

1000: 0.6173

2500: 0.4639

8396: 0.2931

LCC %	LCC	%Max%	%MW
56.85	34.8	2.00	61
56.00	51.4	3.00	92
55.13	67.5	4.00	122
54.24	83.0	5.00	153
53.33	97.9	6.00	184
52.41	112.3	7.00	214
51.47	126.0	8.00	245
50.51	139.1	9.00	275
49.55	151.6	10.00	306
48.58	163.5	11.00	337
47.60	174.8	12.00	367
46.62	185.4	13.00	398
45.63	195.5	14.00	428
44.65	205.0	15.00	459
43.68	213.9	16.00	490
42.71	222.2	17.00	520
41.76	230.0	18.00	551
40.81	237.3	19.00	581
39.88	244.1	20.00	612

PPLR	Sx60	Sx70	Sx80	Sx90	Sx100	S'
1.0	0.18	0.28	0.38	0.48	0.58	1.00
2.0	0.18	0.28	0.38	0.48	0.58	1.13
3.0	0.18	0.28	0.42	0.56	0.70	1.64
4.0	0.22	0.38	0.53	0.69	0.85	2.03
5.0	0.27	0.44	0.60	0.77	0.93	2.42
7.5	0.34	0.52	0.70	0.89	1.16	3.39
10.0	0.46	0.69	0.93	1.24	1.54	4.60
15.0	0.93	1.23	1.62	2.01	2.40	6.19
20.0	1.26	1.64	2.10	2.55	3.00	7.50

Load	%PV	Weight	Cases
100- 90	15.8	0.95	449
90- 80	14.4	0.85	449
80- 70	12.5	0.75	449
70- 60	8.1	0.65	449
60- 50	8.9	0.55	449
50- 40	9.6	0.45	449
40- 30	11.9	0.35	449
30- 20	12.5	0.25	449
20- 10	5.7	0.15	449
10- 0	0.5	0.05	451

Weighted Energy Worth: 59.343

Utility energy output (MWH): 7692255

Total PV: 1616296

Highest considered load: 3060 MW.

Highest overall load: 3060 MW.

Probability of Maximum Peak Reduction

10: 0.6073

25: 0.6235

50: 0.6328

250: 0.5856

500: 0.5710

1000: 0.5386

4492: 0.3598

LCC %	LCC	%Max%	%MW
50.66	125.3	2.00	247
49.64	184.2	3.00	371
48.61	240.5	4.00	495
47.58	294.3	5.00	618
46.53	345.4	6.00	742
45.49	393.9	7.00	866
44.45	439.8	8.00	990
43.41	483.2	9.00	1113
42.37	524.1	10.00	1237
41.35	562.6	11.00	1361
40.34	598.8	12.00	1484
39.34	632.7	13.00	1608
38.37	664.4	14.00	1732
37.41	694.1	15.00	1856
36.47	721.8	16.00	1979
35.55	747.6	17.00	2103
34.66	771.7	18.00	2227
33.79	794.2	19.00	2350
32.95	815.1	20.00	2474

PPLR	Sx60	Sx70	Sx80	Sx90	Sx100	S'
1.0	0.55	0.65	0.75	0.85	0.95	1.15
2.0	0.55	0.65	0.75	0.85	0.95	1.88
3.0	0.55	0.65	0.75	0.85	0.95	2.26
4.0	0.55	0.65	0.75	0.85	0.95	2.78
5.0	0.55	0.65	0.75	0.85	0.98	3.22
7.5	0.67	0.88	1.14	1.40	1.65	4.12
10.0	1.10	1.44	1.77	2.11	2.45	4.98
15.0	1.68	2.11	2.54	3.01	3.52	6.49
20.0	2.08	2.58	3.09	3.67	4.25	7.77

Load	%PV	Weight	Cases
100- 90	17.0	0.95	840
90- 80	14.8	0.85	840
80- 70	13.2	0.75	840
70- 60	11.9	0.65	840
60- 50	13.4	0.55	840
50- 40	13.6	0.45	840
40- 30	10.3	0.35	840
30- 20	4.3	0.25	840
20- 10	1.4	0.15	840
10- 0	0.1	0.05	847

Weighted Energy Worth: 64.726

Utility energy output (MWH): 62399374

Total PV: 2583808

Highest considered load: 12370 MW.

Highest overall load: 12370 MW.

Probability of Maximum Peak Reduction

10: 0.5398

25: 0.5125

50: 0.5532

250: 0.5401

500: 0.5399

1000: 0.5136

2500: 0.4618

8407: 0.3073

QUANTITATIVE LOAD MATCHING ASSESSMENT LOAD MATCHING GRAPHICAL SUMMARIES

Illustrative examples for:

Consolidated Edison (2-axis tracking, 1988)

Kansas City Power and Light (2-axis tracking, 1988)

Salt River Project (2-axis tracking, 1988)

Florida Power and light (2-axis tracking, 1988)

Load Matching Summary

CONED 2axis 88 M

Load Matching Summary

KCPL 2axis 88

Load Matching Summary

SRP 2axis 88

Load Matching Summary

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16. Abstract (Limit: 200 words) This report describes work performed to estimate the load-matching capability of photovoltaics (PV) for a selected group of utilities in the continental United States. The report provides an initial quantitative estimate of this capability for 20 utilities. This characteristic is important because it may indicate that the effective capacity, hence the value, of PV is higher than is traditionally assigned to such non-controllable, non-dispatchable resources. Load-matching capability is determined experimentally by analyzing the interaction between the load requirements of each utility and the output of locally sited PV systems. This type of investigation requires site- and time-specific insolation data that are not commonly available. Here, the needed data were inferred from geostationary satellite remote sensing of the Earth's cloud cover. A secondary objective of this study was to evaluate the suitability of this approach. The results of this investigation are presented in this report.			
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