TOWARDS REACHING CONSENSUS IN THE DETERMINATION OF PHOTOVOLTAICS CAPACITY CREDIT

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ABSTRACT

This article describes an ongoing effort to reach consensus on the notion of capacity credit for solar power electrical generation. The article presents different methodologies quantifying capacity credit and reports on their intercomparison through experimental case studies. It concludes by reporting the initial results of a consensus-building effort involving the utility industry, the solar industry and government.

1. INTODUCTION

The effective capacity or capacity credit of a power plant quantifies the output of a power plant that effectively contributes to the capacity available regionally (to serve a utility service territory) or locally (to serve a feeder or an end-user). This is different from the plant's capacity factor which represents the ratio of its mean output to rated capacity.

PV resources are non-dispatchable because their electrical output depends on the solar resource that varies over a range of time periods. These solar resource variations, however, are clearly not random and there is an intuitively positive relationship between PV system output and summer peak electricity demand for many locations throughout the U.S. This is because system peaks are, for many utilities, driven by heat-wave cooling demand, and because heat waves are indirectly fed by solar gain, i.e., by the same resource as PV generation.

For demand-side customer-owned PV systems, the local capacity credit may be directly quantified and valued when customers use energy/demand tariffs. For supply-side applications however, the notion of PV capacity credit is the subject of some debate, largely because the notion of "available when needed" is difficult to quantify. Doing so depends on: (1) a methodology and a metric to quantify the capacity credit; (2) the geographical distribution and dispersion of the PV resource with respect to the load it serves, and, (3) the time constant used to define the PV-load relationship.

These factors are not independent, particularly time and geography: For a single centralized PV plant, rapid changes in cloudiness are an important consideration and high frequency data are necessary. However a network of PV plants spanning a service territory or a large T&D sector may be adequately described by hourly data because short term variability is mitigated by bundling systems.

The work presented in this article focuses on methodology as a first step towards achieving consensus on PV generation capacity credit. This is done by (1) establishing a catalogue of possible metrics and methodologies; (2) comparing the methods for three case studies; and (3) reporting on a consensus-building effort involving the utility industry, the solar industry and government institutions.

2. CAPACITY CREDIT METHODOLOGIES

The methodologies presented here fall into four broad categories:

1. Methodologies that measure capacity based on the concept of loss of load probability: The Effective Load Carrying Capability (ELCC)
2. Methodologies based on the analysis of load duration curves: Load Duration Capacity (LDC) and Demand Time Matching (DTIM)
3. Methodologies that build on the synergies that exist between short term storage/load control and PV generation: Solar Load Control Capacity (SLC) and Minimum Buffer Energy Storage Capacity (MBESC)
4. Methodologies based on a preset definition of peak time windows: Time Season Window (TSW)

ELCC: The ELCC metric was introduced by Garver in 1966 [1] and has been used mainly by "island" utilities before the strengthening of continental/regional interconnectivity. The method was applied at Pacific Gas and Electric Company [7]. The ELCC of a power plant represents its ability to increase the total generation capacity of a local grid (e.g., a contiguous utility's service territory) without increasing its loss of load probability.

The ELCC is determined by calculating the loss of load probability (LOLP) for two resources. The first resource is the actual resource with its time-varying output. The second resource is an "equivalent" resource with a constant output [1, 4].

LDC: The Load Duration Capacity is a direct analysis of the load duration curve. The LDC is defined as the mean relative PV output for all loads greater than a threshold defined as the utility's peak load L, minus the installed PV capacity X as illustrated in Fig. 1a, where p is the PV penetration fraction, defined as X / L

DTIM: The Demand-Time Interval Matching method has been pioneered by Tom Hansen [7] based on Tucson Electric Power's (TEP) operation of a centralized PV generation facility. While the details of this method are provided in [7], its essence is illustrated in Fig. 1b: Over a given evaluation period, the method examines the worst-case output of the PV system by subtracting the PV system output from the load (in the TEP study this is done over 10 second dispatch cycle time intervals). The capacity credit is based on the worst-case difference between the load duration curves sampled at the dispatch cycle rate over the selected evaluation period. As shown in Fig. 1b, the capacity credit may be expressed as DTIM = Z / X, where Z = (L – L') , with L representing the highest point on the load duration curve for the considered evaluation period and the selected sampling rate and L' representing the top of the same duration curve minus coincident PV output.

SLC: The Solar Load Control metric is illustrated in Fig. 1c. It answers the basic question: Given a certain amount of Demand Response (DR) available to a utility, how much more guaranteed load reduction is possible if PV is deployed?

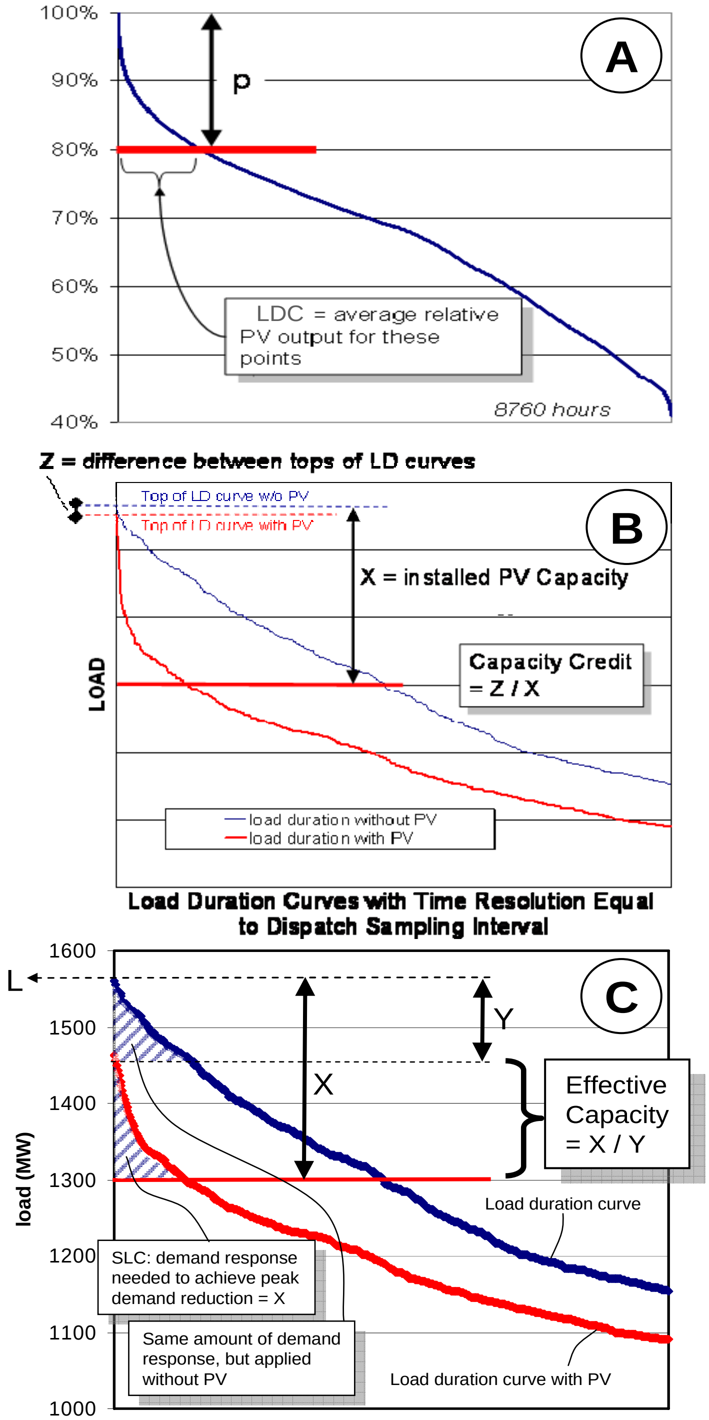

Figure 1: Illustration of the LDC metric (A), the DTIM metric (B) and the SLC metric (C)

Given a penetration $p = X / L$, the effective capacity is given by: $SLC = (X – Y) / X$, Where Y is the amount of load reduction achieved in the absence of PV, but with the same cumulative amount of DR needed to achieve a load reduction of X with PV.

MBESC: This metric is similar to the SLC metric, except that it is quantified in terms of minimum storage requirements – the minimum buffer energy storage, MBES, concept [8, 9] – rather than cumulative DR requirements. As above the metric is an answer to the question: Given a certain amount of dispatchable storage available to a grid or substation operator, how much more guaranteed load reduction is possible if PV is deployed?

Given a PV penetration of $p = X / L$, the method quantifies the minimum amount of storage necessary to guarantee that PV-plus-storage meets all loads above the threshold defined above for the LDC and SLC metrics. The MBES capacity is obtained from: $MBESC = (X – Y') / X$, where Y' is the peak load achieved using the same amount of storage but without PV.

TSW: The Time/Season Window method calculates capacity credits across predefined hours, months, and/or seasons. It is often cited as the ERCOT method, named after the practice to assign capacity credit to wind generators operating in the ERCOT regional reliability council. This practice is also used by the MAPP grid operator.

There are several possible variations on the calculation. The ERCOT method predefines a peak demand time frame – e.g., May-October 10am -6PM – and defines capacity as the minimum output likely to occur with a probability (8% n the case of ERCOT). MAPP utilizes a median capacity value across a monthly 4-hour window. Because it only depends on a preset time window, the TSW metric cannot account for grid penetration. In the following case study section, we analyze the TSW metric using the ERCOT assumption.

Variable Generating Capacity in Practice: The wind industry, being at a much larger penetration scale within the electric grid, has more practical examples of variable generating capacity being utilized by utilities and system operators for generation resource planning. An article in the Electricity Journal in 2006 [10] provided a summary of the practical status of wind capacity credits and showed a fair degree of acceptance for the ELCC method.

3. CASE STUDIES

Preamble: the focus of this paper is on the methodology. However, time frequency and geography issues are central to how any of the methodologies are applied. The issue is briefly discussed here in order to put the case studies into a proper context

The three most important input variables affecting use of and value of a metric are:

- The time frequency , i.e., the time frequency necessary for capturing and analyzing a system's output in relation to its load (e.g., 10 seconds or one hour)
- The number of considered generators, i.e., whether and how to incorporate two or more distinct PV installations.
- The geographical footprint, i.e., the geographic area for analyzing two or more PV installations.

The case studies are based on the analysis of experimental hourly system load demand and PV generation data. They are designed to provide quantitative support to compare the methods in the context of utility-wide PV generation. This assumption, implying multiple systems deployed over an extended geographical area, justifies the use of an hourly data frequency. While the time-geography question will require considerably more analysis, preliminary evidence shows that this assumption is sound. Compare for instance the one-minute irradiance data at a single site from the ARM radiation network in northern Oklahoma [11] on a partly cloudy day, to the bundled irradiances of the 20 ARM stations dispersed over a region the size of a utility territory (Fig. 2). Although the use of hourly data would miss critical variability for the single system, it becomes perfectly appropriate for the ensemble of 20 systems.

Case Studies: We selected three dissimilar utilities for the case studies and analyzed one year of load and PV generation data (2002) for each.

- Nevada Power (NP)
- Rochester Gas and Electric (RG&E)
- Portland General (PG)

Nevada Power (NP) is a metropolitan utility in an arid western state, with considerable solar resource and a large commercial air-conditioning demand. NP is summer-peaking utility by a wide margin (1. 93 summer-to-winter peak load ratio in 2002). Rochester Gas and Electric (RG&E) serves a medium-sized industrial city in upstate New York, where cloudy conditions are not infrequent. The utility also peaks in summer, with peaks driven by daytime industrial and commercial air conditioning, but not to the same extent as NP. RG&E's summer-to-winter ratio was 1.32 in 2002. Portland General serves the city of Portland, Oregon and vicinity. It has been a winter peaking utility until recent years, but now experiences more frequent summer peaks due to increased air conditioning demand and

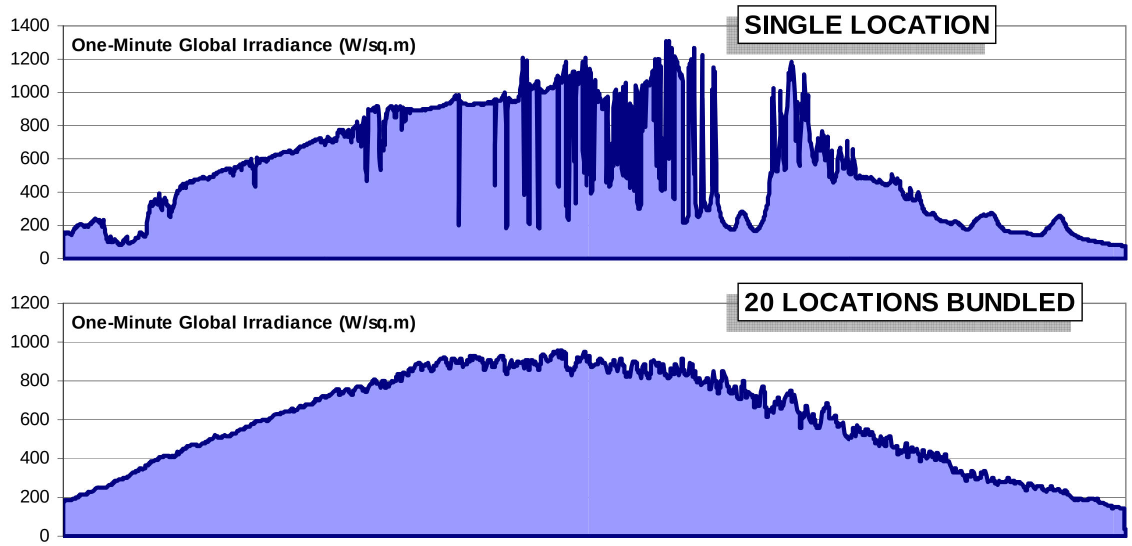

Figure 2: Comparing the solar irradiance at one single location on a single partly cloudy day in the ARM network to that of twenty locations in a ~ 100 miles region on the same day.

a general climatic trend to warmer summers. PG's summer-to-winter peak ratio was 1.01 in 2002.

PV output was simulated for fixed systems facing southwest at 30^{o} tilt, with penetrations ranging from 1% to 20% for each utility. As mentioned above, installed PV capacity is quantified in terms of ac-ptc conditions.

Comparative results for all metrics are presented in Fig. 3. The most striking observation is that all the metrics that are based on a physical measure of PV penetration – ELCC, LDMC, MBESC, SLC and DTIM – provide comparable measures of capacity credit (except for low penetration in Portland, where capacity credit is, in any case, marginal).

The TSW metric provides a considerably different measure of capacity credit. With no dependence on penetration, it is unreflective of any load-PV relationship. This is understandable because within an arbitrarily predefined peak time window, there are many occurrences when the load is small and when reliance on PV output is not critical. Even though there is a significant probability (8% in this case) that PV output could be low during this predefined window, this occurs at time when the load is far from its physical peak. It is thus arguable that the TSW metric is not an appropriate measure of PV capacity credit - no more than the capacity factor should me a measure of capacity credit.

Selecting between the other metrics is not a critical choice, because they do provide comparable results. The authors have a preference for either SLC or MBESC, because these measures eliminate the risk associated with a non-dispatchable resource and introduce the notion of firm power delivery (100% reliability).

The ELCC offers a slightly more conservative estimation of capacity. However, one of the factors defining this metric, the Garver capacity factor m would have to be locally determined, or standardized across-the-board. A value of m = 3% of peak load was selected here, indicating that a peak demand increase of 3% results in almost a tripling of the loss of load risk (see discussion in [4]).

The DTIM metric shows more discontinuity than other metrics when plotted against penetration; This is because it is based on one single critical point at the top of the load duration curve and this point may shift significantly depending on the relative size of the PV generation.

4. ACHIEVING CONSENSUS

The first step taken towards reaching consensus was the presentation and discussion of the methods and case studies at the PV Capacity Workshop held on during the Solar Power 2007 conference [12]. The workshop included a solid mix of utility, government and solar industry representatives.

Focusing on methodology was a challenge because the question of capacity itself brings related issues to the table including: The monetary value of capacity, the differences between emergency planning, capacity planning, and ancillary services, the cost of PV, planning for future penetration of PV, the question of ownership, what happen at very high penetration levels, etc. However, the workshop did succeed in focusing on methodology and was concluded by a straw poll on metric preference. Results are presented in Fig. 4. Note that, for this straw poll, the SLC and MBES methods were combined because of their operational similarity.

The ELCC was the preferred method overall, followed by the MBES/SLC method. There was a clear distinction however, between utility and solar industry preferences, with utilities preferring the more familiar ELCC, while the solar industry preferred the methodologies exploiting control/storage synergies and eliminating the notion of risk associated with non-dispatchable PV generation.

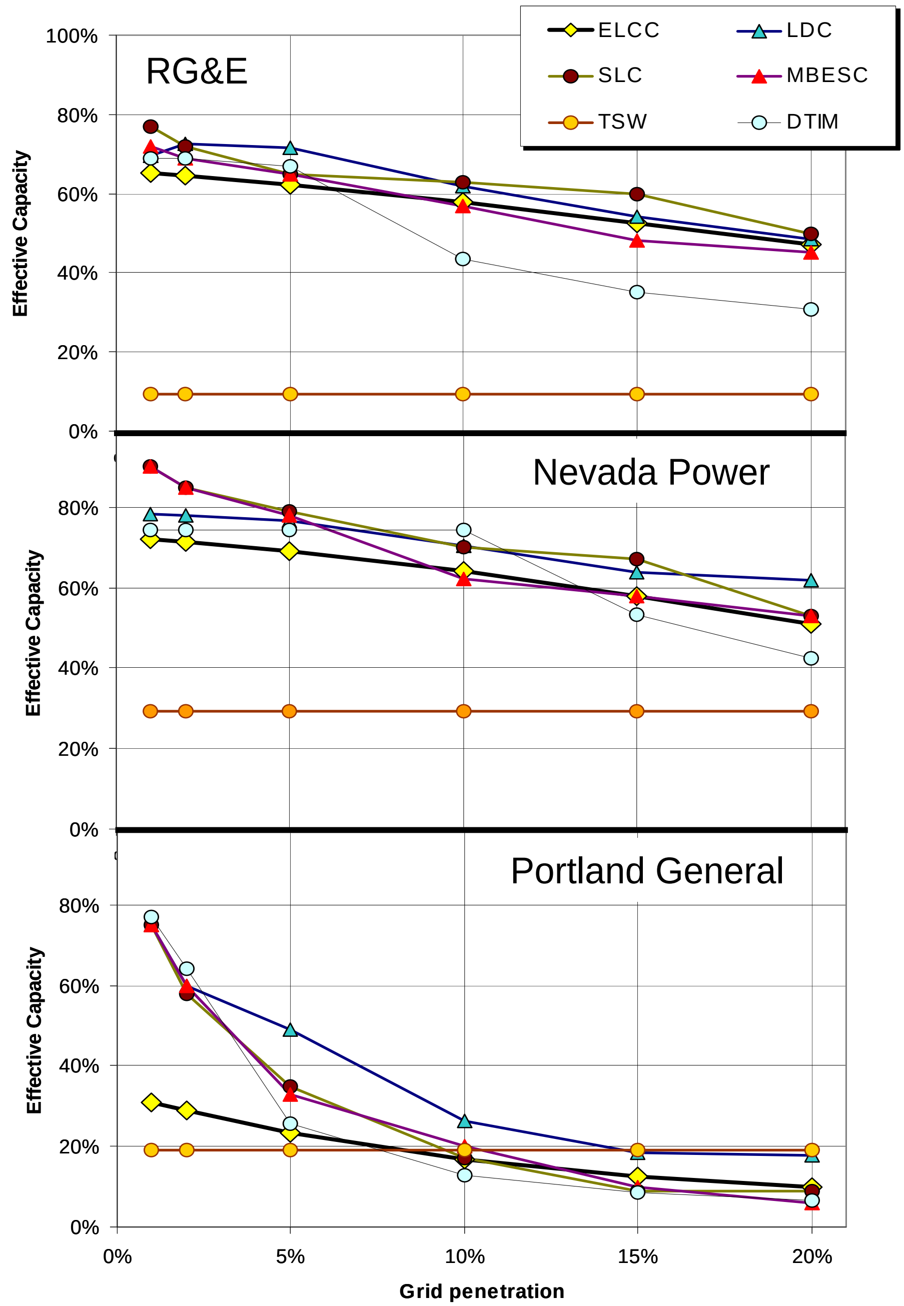

Figure 3: Comparing capacity credit metrics as a function of PV penetration

5. CONCLUSIONS

One of the important findings of this study is that all methodologies that account for the physical penetration of PV and its impact on load demand are in general agreement on the determination of capacity credit. Methodologies that are based on an arbitrary definition of a peak demand time frame lead to different results.

While there is a general agreement on most methods' result given identical input, the study suggests that that the geographical and time context of PV generation must be clearly defined. Hourly sampling rates appear to be appropriate to quantify the impact of dispersed PV generation over a large foot print, but may be insufficient to characterize capacity for a single plant serving a small area. However, because methods such as SLC or MBESC bundle control/storage as an assumption of capacity determination, they should be considerably less sensitive to the time/geography context than methodologies like DTIM or ELCC.

A panel of utility industry, solar industry and government representatives identified the ELCC and SLC methodologies as the two preferred approaches, while noting a distinct shift in preference between utilities, preferring the ELCC method, and the solar community preferring the SLC method.

6. ACKNOWLEDGEMENT

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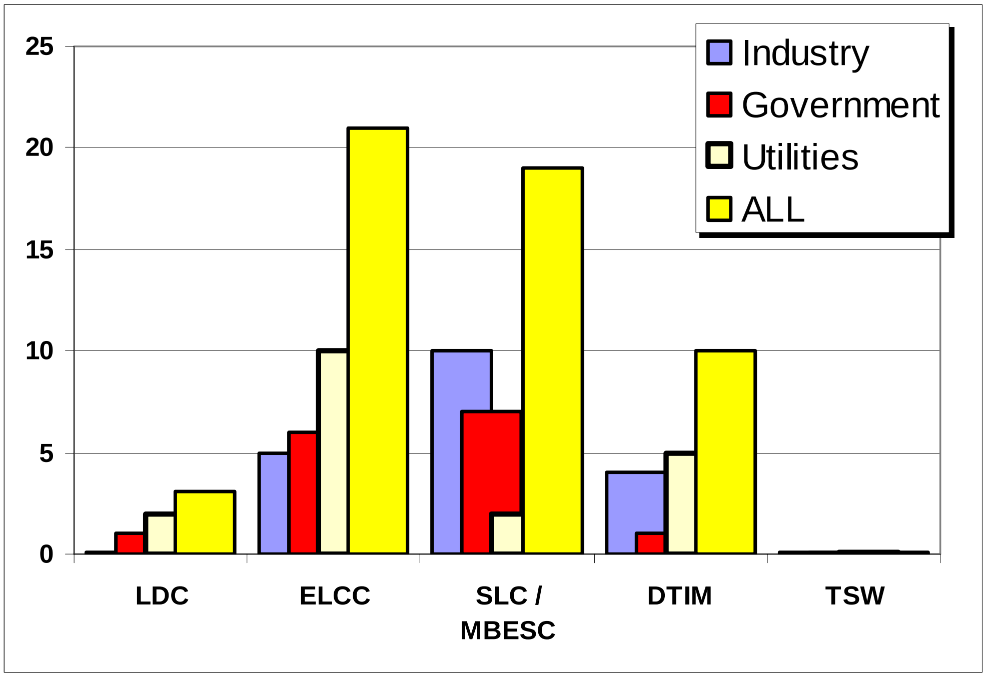

Figure 4: Results of the straw poll on methodology preference

7. REFERENCE

1. Garver, L. L., (1966): Effective Load carrying Capability of Generating Units. IEEE Transactions, Power Apparatus and Systems. Vol. Pas-85, no. 8
2. Hoff, T, (1988): Calculating Photovoltaics' Value: A Utility Perspective, IEEE Transactions on Energy Conversion 3: 491-495.
3. Kapner M., (1990): Personal Conversation, New York Power Authority
4. Perez, R., M. Taylor, T. Hoff, and J. P. Ross, (2008): Moving Toward Consensus on a Photovoltaic Generation Capacity Valuation Methodology. USDOE Technical Report on Contract DE-FC36-07GO17036, published by SEPA , Washington, DC.
5. Perez, R., R. Seals and R. Stewart, (1993): Assessing the Load Matching Capability of Photovoltaics for US Utilities Based Upon Satellite-Derived Insolation Data, IEEE Transactions, pp. 1146-1149 (23d. PV Specialists, Louisville, KY)
6. Perez, R., R. Margolis, M. Kmiecik, M. Schwab and M. Perez, (2006): Update: Effective Load Carrying Capability of Photovoltaics in the United States. Proc. ASES Annual Conference, Denver, CO
7. Tom Hansen, (2007): Utility Solar Generation Valuation Methods, Personal Communication, Tucson Electric Power, Tucson, AZ.
8. Perez, R., R. Seals and R. Stewart, (1993): Solar Resource - Utility Load Matching Assessment. Phase One Final Report to the Natl. Renewable Energy Lab. (24 pp.). NREL/TP-411-6292, NREL, Golden, CO
9. Perez, R., C. Herig, R. Mac Dougall, and B. Vincent, (2002) Utility-Scale Solar Load Control, Proc. UPEX 03', Austin, TX. Ed. Solar Electric Power Association, Washington, DC
10. Milligan, Michael and Kevin Porter. The Capacity Value of Wind in the United States: Methods and Implementation. The Electricity Journal. March 2006, Vol. 19, Issue 2
11. Stokes, G. M. and S. E. Schwartz, (1994): The Atmospheric Radiation Measurement (ARM) Program: Programmatic Background and Design of the Cloud and Radiation Test bed, Bull. Amer. Meteor. Soc., 75, 1201-1221
12. Photovoltaic Capacity Workshop, Solar Power 2007 Conference, Long beach California.