BUILDING A BANKABLE SOLAR RADIATION DATASET

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ABSTRACT

In order to obtain financing at a competitive interest rate, and therefore ensure the best economics of a solar project, a bankable solar radiation dataset is required. Almost all solar radiation datasets are derived from publically available data, and the strengths and weaknesses of these existing solar radiation databases are discussed herein. While the financing community generally views the solar resource as stable, it also views the material miscalculation of the solar resource as one of the biggest risks in a solar project. Therefore, lenders and rating agencies alike require verification of the solar resource dataset to be utilized at each project location (as this translates directly into electric energy production forecast and revenues) as well as analyses of historical solar resource variability and probability.

1. INTRODUCTION

All indications are that solar installations are expected to continue to grow, and recent trends show an appetite for large-scale utility installations[†]. With the solar industry on the verge of contributing meaningfully to the energy mix and the need for cost competitive financing, these facilities seek non-recourse loans, and these types of loans require that they be critically evaluated much the same as any traditional IPP (independent power producer) electric generating facility (e.g., gas turbines, etc.).

In the mid-1980s, solar thermal electric systems in the 5- to 30-MegaWatt (MW) size were built; however, over the next 20 years there was a hiatus in building large solar thermal electric facilities. Ten years ago, photovoltaic (PV) systems in the 5- to 25-kiloWatt (kW) range were considered large systems and only five years ago, PV systems in the 100- to 500-kW range were considered huge. Today, there are PV solar generating facilities larger than 10 MW in size, and plans for both PV and solar thermal electric facilities in the 100- to 500-MW range are under consideration.

Initially, small solar generating facilities were financed by home owners or on the balance sheets of commercial companies. Tax credits and incentives helped make systems more affordable, and company image was a higher priority than a solar system's installation cost and performance. As total installed costs have decreased and stimulus increased, there has been a broader market appeal for installing solar systems as there is economic justification based on the estimated rate of return (with subsidies). Additionally, certain regions are required to meet renewable and/or solar energy portfolio standards that have prompted utilities to either build their own solar generating facilities or, more often, enter into firm off-take agreements for the delivery of electric energy from large or utility-scale solar generating facilities. As a result, financing has emerged as an important consideration in deploying a solar generating facility and meeting the needs of the financing parties. While there are many considerations in solar generating facility financing, the key considerations include capital cost and system performance (which is largely based on the available solar resource).

While total financial viability of a solar project is paramount for any size of project, this is especially true for the utility - scale solar projects that are now being submitted to banks, bonding companies, and even the U.S. Department of Energy under its various programs for financing. While there are

[†]For purposes of this paper, a utility-scale facility is as any facility with a capacity at or greater than 21 MW, as this is usually the size in which an installation must obtain a Large Generation Interconnection Agreement and complete a transmission study.

many factors considered when these institutions evaluate the ability of the project to repay its loan, the sale of the generated electricity is one of the most-important factors for assessing a project's viability and ability to repay its debt.

In order to have a successful financing, a thorough and rigorous evaluation of the solar resource suitable for a project's proposed technology is required. To effectively analyze the solar resource, one needs to evaluate more than just the average irradiance available at the proposed site. In addition, knowledge is required on how the availability of the resource varies over a day, month, year, or the duration of the project life, especially for projects with off-take agreements where there is a time-of-day pricing component. Furthermore, plant design and operational planning benefit from a detailed understanding of the solar resource fueling the plant.

This paper discusses the development of a sound, bankable dataset and the nature of the uncertainties in the various constituents of the data. First, the issues of concern from a financial perspective are briefly reviewed to give context to the discussions on the solar resource dataset. The next section evaluates the ability of various existing datasets to address these issues. The Typical Meteorological Year (TMY) data files are suitable for initial evaluations, but typically do not necessarily constitute a bankable dataset. Specific examples are given to illustrate the limited value of TMY files and why it is necessary to utilize the long-term databases from which the TMY files were created. This includes evaluating the data files in the National Solar Radiation Data Base (NSRDB). Next, the importance of measured data is examined and the method to connect measured data with a longer-term database is presented. Lastly, the building of a bankable dataset from the NSRDB and other available datasets is illustrated and the use of the dataset is described and the key features are summarized.

2. THE FINANCIAL PERSPECTIVE

In pure market terms, most large or utility-scale solar generating facilities usually require a regulatory or above-market firm off-take agreement to support cash flow projections for debt repayment. Of utmost importance to a lender is how the project provides and maintains cash flow over the debt term and its ability to meet certain lending covenants including debt service coverage ratio (DSCR). Key factors that lenders consider in evaluating a project's ability to repay its debt include not only the stability and financial cost and performance of the project owner and credit worthiness of the off-taker, but also the ability of the project to maintain adequate cash flow under potential down side scenarios (or stress cases).

The key consideration in debt repayment is the robustness of the revenue stream. This is a direct product of the electric energy rate being paid by the off-taker and the solar generating facility's electric energy production, which of course is reliant on the solar resource. Unlike fossil-fuel generating facilities, solar generating facilities cannot control their fuel input and the variation of the fuel resource, which lenders recognize as risks associated with solar generating facilities. Knowledge of the amount, timing, and variability (including historical lows) of the solar resource influence the amount of electricity produced, and thus the revenue stream.

Therefore, it is crucial to understand the variability of the resource from year-to-year. In addition, as solar resource varies with seasons, it is also important to know the variability of the resource season-to-season not only to accurately project cash flow on a quarterly basis (which is a typical lender requirement), but also to properly evaluate design and maximize revenues if the off-take agreement has time-of-day and/or seasonal pricing components. Additional key components obtained by evaluating the solar resource and ultimately energy projections include the mean power generation projections and the minimum and maximum projected generation during a season. The mean power produced often determines the viability of the project; however, lenders may choose to size debt based on a P90 forecast (as discussed in more detail in section 6). The forecast minimum power produced provides a minimum threshold in which the project must be able to meet a 1.0x DSCR, or slightly higher, or debt sizing may be reduced. This threshold sensitivity allows lenders to become comfortable that even under predicted "worst case" solar resource availability that the project will be able to meet the loan payment schedule. The maximum power production shows the range of generation that needs to be accommodated for the design of the project. Many other factors such as the persistence of sunny or cloudy weather and the dependability of the system to produce electricity over certain times of day in certain months are also important.

While the facility's theoretical generating capacity is specific to the type and size of the solar facility, it is the historical solar resource data input into the system performance model that emulates the amount of electricity that will actually be produced. Therefore, it is important to have a reliable, well-characterized solar radiation dataset.

3. TMY FILES AND THE NATIONAL SOLAR RADIATION DATA BASE

Typical Meteorological Year data files were first created from long-term data files in the National Solar Radiation Data Base (NSRDB) to help with the analysis of building performance at a time when computers were much slower and had smaller memory banks than today. Users wanted a one-year dataset that would emulate the results produced by using the thirty years of available data in the NSRDB. Many of the meteorological data parameters affected performance more than the incident solar radiation, and the TMY data sets were created to be "typical" of the meteorological data contained in the NSRDB.

Each TMY data file consists of a full year of data constructed from twelve months chosen as most typical from the years that made up the data base. The original TMY data files were created by Sandia National Laboratory using a method in which a typical month was selected based on nine daily indices consisting of the maximum, minimum, and mean dry bulb and dew point temperatures; the maximum and mean wind velocity; and the total global horizontal irradiance (GHI) (See Table 1). Final selection of the month included consideration of the monthly mean and median of the nine indices shown in Table 1 and the persistence of weather patterns [1]. The twelve candidate months were then concatenated to form the representative TMY file. Modifications were made at the beginning and end of each month to smooth the transition caused by selecting adjacent months from different years.

The original TMY data files were created from measured GHI SOLMET data and modeled ERSATZ data from 1952 to 1975. TMY2 data files were created from the 1961 to 1990 NSRDB where 93% of the values were modeled data. TMY3 data files were created from 1991 to 2005 NSRDB data plus the 1961 to 1990 NSRDB data if it existed for that location. For the TMY2 data files, the direct normal irradiance (DNI) was added to the weighting indices. This improved the comparison of the annual average DNI in the TMY file to the long-term DNI average in the NSRDB files by approximately a factor of two. The weighting for wind speed was reduced and the criteria for persistence were altered slightly in the TMY2 and later TMY3 data files [2]. Table 1 shows the difference in weighting used in Sandia (TMY) and NREL (TMY2 and TMY3) methods. Note that half of the weight was placed on solar irradiance values and the other half was on meteorological parameters.

For the original TMY data files, the monthly mean daily total GHI and DNI, from measured SOLMET data, have an estimated uncertainty of ±7.5% and ±10% respectively. Similarly, the monthly mean daily total GHI and DNI, from the modeled ERSATZ data, have an uncertainty of ±10% and ±20%, respectively [9].

For the TMY2 files, the months from May 1982 through December 1984 were excluded from the analysis because the aerosols from the eruption of El Chichón, Mexico differed significantly from typical values. For TMY3 files, the months from June 1991 to December 1994 were excluded

Table 1: WEIGHTING OF METEOROLOGICAL PARAMETERS

Index	Sandia Method	NSRDB TMY
Max Dry Bulb Temp	1/24	1/20
Min Dry Bulb Temp	1/24	1/20
Mean Dry Bulb Temp	2/24	2/20
Max Dew Point Temp	1/24	1/20
Min Dew Point Temp	1/24	1/20
Mean Dew Point Temp	2/24	2/20
Max Wind Velocity	2/24	1/20
Mean Wind Velocity	2/24	1/20
GHI	2/24	5/20
DNI	Not Used	5/20

because the aerosols from the eruption of Mount Pinatubo, Philippines were atypical. As a result of the exclusion, 83% of the TMY3 files were derived using 11.5 years of data.

3.1 Limitations of the TMY2 and TMY3 Files

The TMY files were created to represent typical meteorological years and not typical solar years. Due to the limited number of years in most TMY3 data files, there is no guarantee that the TMY3 file will be an accurate representation of the average GHI or DNI for the entire historical data set. Examples where the GHI and DNI TMY annual average are different from the NSRDB average are shown in Figs. 1-2. For example, at Groton-New London, CT, the annual TMY GHI is below the yearly average GHI for every single year in the NSRDB. A moving average was used and no 12-month period has an annual GHI as low as the TMY3 file. This moving average approach takes any consecutive twelve month period and generates annual average values. For example, it averages January through December, then February through January of the following year, then March through February of the next, etc. to generate the yearly averages. For Paso Robles, CA, the opposite is true. The GHI of every single 12-month period is below the annual average TMY3 GHI.

Figs. 1-2 also show the DNI for Groton-New London, CT, and Paso Robles, CA. These two examples illustrate that even when 50% of the indices weighting is GHI and DNI, there is no guarantee that the annual average irradiance values obtained from a TMY file will closely represent the true long-term average solar irradiance.

The TMY dataset purposely excludes extreme events and therefore is of no use when trying to understand resource variability (and for that matter obtain the P90 or P95 levels of confidence as discussed in section 6).

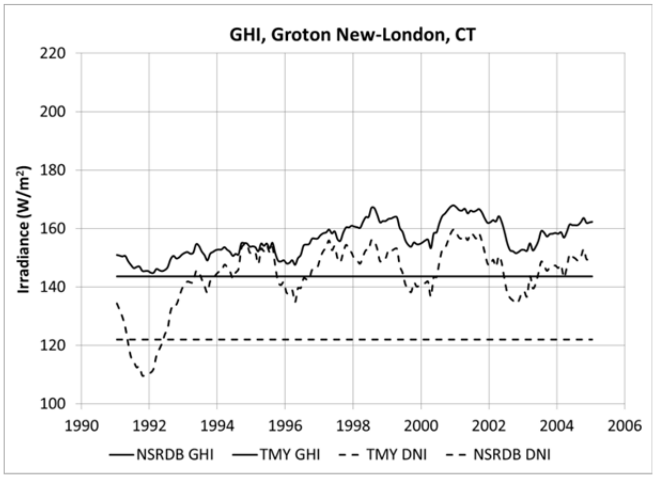

Fig. 1: Plot of GHI and DNI for Groton-New London, CT. The straight solid line is annual average GHI from the TMY3 data file and solid line is the annual average GHI from the NSRDB data file. The dashed straight line is the annual average DNI from the TMY3 file and the dashed curved line is the annual average DNI from the NSDB file.

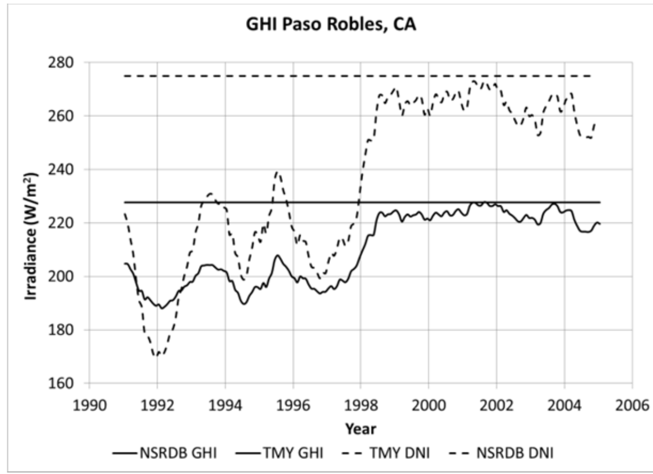

Fig. 2: Plot of GHI and DNI for Paso Robles, CA. The straight solid line is annual average GHI from the TMY3 data file and solid line is the annual average GHI from the NSRDB data file. The dashed straight line is the annual average DNI from the TMY3 file and the dashed curved line is the annual average DNI from the NSDB file.

As with meteorological variables, it takes approximately thirty years of data to fully characterize the solar irradiance statistics for a site. By using thirty years of data all of the shorter-term weather variations are included, such as those caused by El Niño and La Niña episodes, or even the 11- or 22-year sun spot cycle. These shorter cycles definitely influence the resulting means or persistence measures. For shorter time intervals, such as 15 years, the likelihood increases that weather cycles such as El Niño events will skew the statistical characteristics.

4. NSRDB'S STRENGTHS AND WEAKNESSES

The NSRDB is a solar radiation database maintained by NREL. The NSRDB can be divided into two sections. The older NSRDB consists of solar radiation and meteorological values from 1961 through 1990 for 239 sites [3]. While there are some sites with measured irradiance data, the NSRDB consists mainly of modeled values determined using the METSTAT model [4]. The METSTAT model uses cloud cover, aerosol, and other meteorological data to calculate the incident GHI and DNI values that are statistically similar to actual measured hourly irradiance data. While some minor problems have been identified in the METSTAT model that affect irradiance estimates during very cloudy periods [5], this model produces an irradiance dataset that is a good statistical match to actual measured irradiance data.

When all the meteorological and aerosol data are available, METSTAT data have an uncertainty of ±9% at the 95% confidence level. There are periods in the NSRDB where the meteorological values have had to be extrapolated, and these periods have a higher uncertainty.

Any long-term climate change trends in the irradiance data have been obscured by the nature of the METSTAT model and of the assumptions used to generate the irradiance data. In addition, trends are disguised by systematic errors resulting from the uncertainty in the meteorological data and from systematic errors in the irradiance data used to validate the model. The uncertainty of the GHI data derived using the METSTAT model is 9%. However, this does not mean that the NSRDB hourly GHI value is within 9% of the actual GHI value 95% of the time. It means that *true average GHI* that would result from several measurements under similar conditions should lie within nine percent 95% of the time [5].

The NSRDB data have been generated for 1,454 stations during 1991-2005. From 1998 to 2005, the data values were derived with models using satellite images and other meteorological and auxiliary data [6]. Most of the early data values, before 1994, were derived using the METSTAT model with the improvement suggested in [5] to produce better statistics during very cloudy weather. From about 1994 to 1998, cloud height and other data from the surface weather observation stations (ASOS/AWOS) were used as input to a modified METSTAT model to produce irradiance values. In an attempt to produce a serially compete dataset, some of the input data were modeled from nearby stations in cases where records were incomplete or missing. The data produced with modeled input data have a higher uncertainty

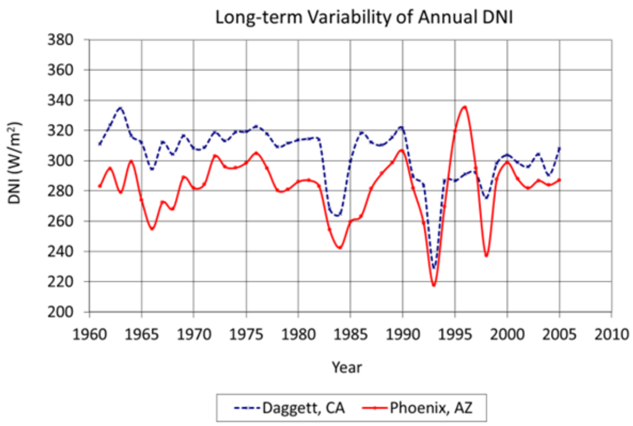

Fig. 3: Long-term variability for Direct Normal Irradiance at Daggett, CA and Phoenix, AZ.

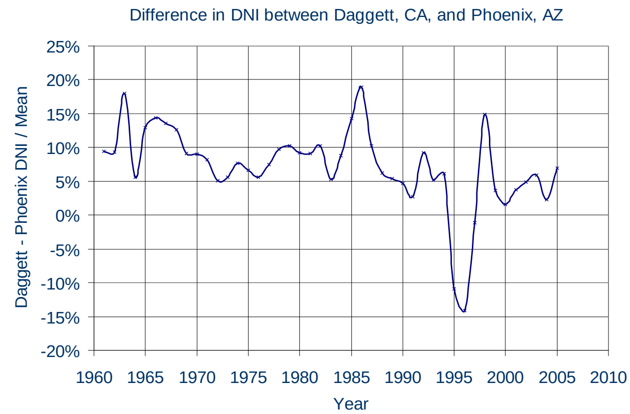

Fig. 4: Percent difference between annual DNI for Daggett, CA, and Phoenix, AZ. On average the Daggett DNI is about 7% greater than the Phoenix DNI and 95% of the years are within ±10% of the average.

flag, and some values have uncertainties as high at 24% for GHI and 27% for DNI. Therefore, one should always check the uncertainty flags with the data.

Starting in 1998, satellite-derived irradiance values became available for all sites in the NSRDB, and the records were very complete. As a result, satellite derived irradiance data have been produced for all sites in the NSRDB from 1998 through 2005. The NSRDB also contains the ASOS/AWOS modeled data as well as some measured data for those sites with high quality measured data that are co-located or near the ASOS/AWOS stations. The ASOS/AWOS stations are automated weather stations located at or near airports.

The satellite-derived data produced by the State University of New York (SUNY) at Albany was obtained from images taken once per hour [7]. The images were from the GOES weather satellites and only the visual channel images were used. The SUNY satellite-derived data is on a 0.1-degree grid; roughly a 10-km grid. The GOES west images in the SUNY data set were taken 30 minutes after the hour and GOES east images were taken 45 minutes after the hour. (Today the GOES satellites produce images every half hour.) To integrate the satellite derived data into the NSRDB, the satellite images had to be shifted either one half hour or fifteen minutes so that they were coincident with the meteorological data in the dataset. The solar data was then merged with the ground station data. The averaging process is explained in the NSRDB user manual [6]. The time shifting increased the uncertainty in the data by 1 to 2%. This uncertainty is typically a random error that averages out over time. The uncertainty for the satellite-derived GHI is 8% and the DNI is 15% at the 95% confidence level. Again, this refers to the uncertainty against the average of several GHI or DNI measurements made under similar circumstances. A thorough discussion of the uncertainties in the NSRDB data can be found in the user manuals [5, 6].

New models for deriving irradiance data from satellite images are currently being evaluated. Most models use the data from the visual spectrum channel. The GOES satellites also measure irradiance at other wavelengths, such as IR, and newer models are starting to incorporate data from these other channels. There are several companies now that produce irradiance data from satellite images. These analyses are being automated and some companies are forecasting the solar resource with the aid of satellite data.

5. NASA'S SURFACE METEOROLOGY AND SOLAR ENERGY DATA

The NASA's Atmospheric Science Data Center provides 22 years of surface meteorological and solar irradiance data (NASA SSE) going back to 1983. This data set covers the world, with values every 3 hours. Originally the grid size was approximately 2.5 degrees, but recent efforts have provided data on a 1.0-degree grid [9].

A 1.0-degree grid is not fine enough for evaluating the irradiance at a single site, but the long-term nature of the data is very useful. Figures 3 and 4 compare the GHI for Phoenix, Arizona and Daggett, California from 1961 through 2005 using data from the NSRDB. For the most part, the data from the sites is very consistent, with the GHI at Daggett between 5 and 10 percent higher than in the Phoenix area. Only the data between 1995 and 1998 deviated from that trend. The Phoenix data between 1995 and 1998 have uncertainties as high as 24% for the GHI.

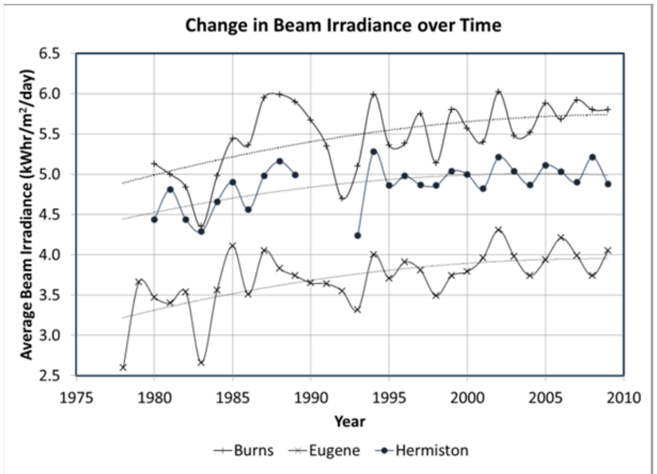

Fig. 5: Ground-based DNI measurements in the Pacific Northwest from 1978 to 2009 show about a 10% increase over thirty years. The GHI increase is only a few percent and is within GHI uncertainty estimates.

In general, the two sites, while hundreds of miles apart, do exhibit similar trends. The sites within the 1.0-degree grid generally exhibit the same trend while the mean values may differ. Therefore, long-term trends that show up in this NASA/NOAA dataset are probably representative of the data from the sites in the gridded area.

6. GROUND-BASED IRRADIANCE DATA

Under optimal maintenance conditions, the uncertainty in ground-based solar radiation is ±5% for GHI, ±3% for DNI, and ±7% for diffuse horizontal irradiance (DHI). To achieve these uncertainties, the domes and windows of the instruments must be cleaned on a regular basis, the pyrheliometer for the DNI measurement must be aligned properly with the sun, the DHI must be measured using a shade disk, and the instruments must be calibrated regularly. The studies show that a Rotating Shadowband Radiometer (RSR) yields DNI with an uncertainty of ±5% [10].

Note the caveat that the instruments must be well-maintained. If a solar monitoring station is set up and left without maintenance, the uncertainty in the data increases significantly. Long-term data are difficult to find because funding fluctuates over time, and monitoring requires consistent vigilance to obtain good results. It is often difficult to validate long-term trends because long-term trends are small, and consistent calibrations are necessary throughout the length of the database. An example of a long-term trend is shown in Fig. 5. The DNI increased by about 10% at three stations in the Pacific Northwest. The year to year variation of about 5% is one reason it takes a long time to observe a trend with any statistical certainty. Note that it takes nearly all thirty years to build confidence in the trend, and it only clearly shows in the DNI. The DNI is more sensitive than GHI to changes in cloudiness and aerosol density.

7. INFORMATION REQUIRED FOR A BANKABLE SOLAR DATABASE

Planning, design, and financing of a solar project depend on knowledge of the system performance. To estimate system performance one needs to know the solar resource incident on the system, meteorological data that will affect system performance, and the relationship between these resource parameters and system output. In this study, only the solar resource is discussed as it is the primary parameter that affects system performance and often the most difficult one to characterize accurately.

A full description of the revenue stream from the sale of electricity produced by the planned facility is an important component of the financial plan. One of the greatest uncertainties in this revenue stream is the variability of the solar resource that is used to generate the electricity. While it is certainly important to know the expected average energy production of the system, it is also critical to understand the variability of the production from season to season and year to year. Financial institutions often ask what the P50, P90, and P95 or P99 levels of production are, and rating agencies typically use a P90 or P99 production level to rate the viability of the project.

In solar resource assessment a P95 level of production means that the electric energy generated will exceed this level 95% of the time. When doing a financial analysis, it is necessary to know the worst revenue year to be expected so that one can evaluate how well a company can maintain loan repayments during poor resource years. Further, a one-year average should be used because the finance structures of typical projects require them to service the debt once or twice a year, not every five or 10 years. Other factors, such as the financial stability and credit worthiness of the company, are also important.

The amount of the loan and the rate of the loan all depend on the risk perceived by the lender. With larger systems requiring tens or hundreds of millions of dollars to construct, lenders are very conservative in their estimates. While every lender has its specific requirements in sizing a project's debt, lenders typically try to liken the perceived solar resource risk to a confidence level that they feel reflects a typical power production project. This means that we have seen debt sized based on a one-year P50 to P90 with debt service coverage ratios varying from 1.5x to 1.3x, respectively. Besides knowing the variability of the solar resource over time, it is also important to accurately evaluate the uncertainty in the data and provide sound reasoning that validates the level of uncertainty. Therefore it is financially advantageous to provide the most accurate data available.

8. BUILDING A BANKABLE DATASET

Ideally, the most bankable dataset would come from a high-quality site-specific solar monitoring station that is well maintained and the measurements taken over 30 years or longer. However, very few data sets of that duration exist, and the need for short-term profitability places severe constraints on the practicality of undertaking any new and comprehensive studies before seeking funding for a project at a given site. Fortunately there exists a suitable database that helps characterize the solar resource and gives a good idea of the hourly, monthly, and annual incident energy. These data are usually archived in the NSRDB and the National Climatic Data Center (NCDC). The NSRDB contains modeled solar radiation values from 1961 to 1990 for 239 sites and from 1991 to 2005 for about 1,454 locations across the United States. Almost all of the 239 sites in the 1961-1990 NSRDB are represented by sites in the 1991-2005 NSRDB. Daggett, CA and Phoenix, AZ shown in Figs. 3 & 4 are good examples of the longest term sites.

To obtain long-term information for the project site, one has to extrapolate the information from a nearby site that has data in the NSRDB to the project site. Fortunately, NREL also has an archive of satellite-derived data from 1998 to 2005 on a 0.1 degree grid for the United States. In addition, satellite-derived solar radiation data are also commercially available from 2005 to present. Comparing the satellite-derived data from the NSRDB site and the project location helps to accurately extrapolate the NSRDB data to the project site [9]. The information from the NSRDB site provides information on the long-term variability and the comparison of the satellite-derived data between the two sites provides a good estimate of the average solar resource.

A realistic bankable dataset would include 15 to 45 years of data from a one of the sites in the NSRDB. A satellite-derived dataset for the plant location (a 0.1-degree grid resolution would be acceptable) and a neighboring site in the NSRDB would be necessary in order to model the expected performance at the planned power facility site. The satellite-derived data set for 1998 through 2005 is available on the NREL website. It is expected that a few years of additional satellite-derived irradiance values will be added to this database. More current data can be purchased from commercial companies.

The 1983-2005 data from NASA SSE dataset (on a 1.0-degree grid) for the location under study may also be useful. Comparison of the NASA SSE data with the NSRDB database would help identify any potential problems with the modeled NSRDB data if the relative values in the two data sets suddenly deviate. Long-term climate trends may also be visible in the NASA SSE dataset since it is produced in a consistent manner from 1983 to 2005 while in the NSRDB was produced from a number of different models, especially in the 1991 to 2005 time period.

To increase confidence in the dataset and reduce the uncertainty, the bankable dataset would benefit greatly from ground-based measured data. While the mean bias estimates of satellite data are small, on the order of a few percent for GHI, it is useful to have the satellite-modeled data validated by measured ground-based data because there are occasional systematic problems with satellite-derived data for some types of terrain (e.g. dry salt beds, forested areas, etc.) and it is always valuable to confirm that the satellite data are accurate. A minimum of one year's worth of ground-based data can validate the satellite-derived data for the site and provide more stringent uncertainty limits on the data. Of course, concurrent satellite data would have to be purchased for the location. In addition, the current model of the satellite derived data would have to be compared with the historical satellite-derived data in the NSRDB.

The ground-based data should be gathered for time intervals no longer than 15 minutes as such short time-interval data are valuable in designing and operating the facility.

There are two periods in the NSRDB where the irradiance values were affected by volcanic eruptions: 1982-1984 (El Chichón) and 1991-1994 (Mt. Pinatubo). There have been only four major volcanic eruptions during the past 100 years that significantly affected the atmospheric aerosols. Thus, we might expect about one major event over a 25-year life of a solar facility. Therefore, a bankable solar dataset should include data from at least one of these events in the analysis.

9. USING THE BANKABLE SOLAR DATASET

Once the irradiance dataset has been gathered, the performance of the solar system can be calculated through a variety of models. With 15 to 45 years of data, one can then evaluate the minimum, maximum, and average production of the facility. Statistical packages can be used to determine the probability of performance at any level from P50 to P99. The variability of the performance from year to year will be evident, and one can plan for production shortfalls during the cloudiest years. More importantly, the variation in the capacity factor for the facility can be established and the seasonal variability and diurnal variability of the production can be determined. Capacity factor is the annual estimated output of the plant divided by the output of the plant if it ran 24 hours per day, 365 day per year at maximum output.

The long-term data can also be used in developing operational and management plans and assisting in the creation of a forecasting model.

10. SUMMARY

A bankable dataset consists of many years of data, typically between 15 to 45 years to characterize the variability of the resource. It is possible to use a long-term dataset from nearby sites because satellite-derived data sets are available on a fine scale (about 0.1 degree grid, resolving to about 10 km). Long-term satellite-derived data from the NASA SSE is valuable in looking at long-term trends and identifying any inconsistencies in the modeled NSRDB data.

Ground-based measured data enhance the value of the data set by validating the satellite-derived data or showing any possible systematic bias in the satellite data. This requires concurrent ground-based measurements and satellite derived data. The better the ground-based data, the more accurately the bias in the satellite-derived data can be determined. Poorly maintained solar monitoring sites are not much better than satellite-derived data because of the systematic errors that result.

A thorough knowledge of the uncertainties and accuracy of the data set is important. When the production of the system is analyzed for financing, the accuracy affects the risk involved. To compensate for this risk the most conservative values are used.

11. ACKNOWLEDGEMENTS

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