A NEW BUSINESS MODEL FOR GRID-CONNECTED SOLAR GENERATION IN RESTRUCTURED ELECTRICITY MARKETS

James Bing, PE
New Energy Options, Inc.
410 Great Road, B-6
Littleton, MA 01460
jbing@newenergyoptions.com

ABSTRACT

The unique physics and operational characteristics of photovoltaic technology differentiate it from other, conventional, dispatchable energy sources. PV technology differs fundamentally from conventional generation in the way in which it interacts with the electrical grid and with deregulated wholesale electricity markets. This paper seeks to demonstrate that photovoltaic generation, distributed across a region, on the load side of facilities revenue meters

1) can be forecast on a day-ahead, hourly basis;
2) has the ability to be traded in a manner *similar* to other forms energy in wholesale electricity markets;
3) could enable increased market liquidity in the form of derivatives and ancillary services associated with PV energy.

1. INTRODUCTION

Solar irradiance is, on average, on an annual basis, periodic and predictable. However on an hourly basis, on many parts of the earth's surface, solar energy is fundamentally variable. Presently solar energy contributes only a tiny fraction of the electrical energy consumed within the electrical grid. In its present form the electrical grid, both in its physical structure and in its market configuration, is not designed to incorporate a significant percentage of the daily energy transactions from highly variable, non-dispatchable energy sources. With present technology, large amounts of electrical energy cannot be stored cost effectively, and must be used as soon as they are produced. Therefore the electrical grid requires constant management to balance production with demand. As an essential and critical resource for our society, grid reliability standards are extremely high, often referred to as being in the "high nines" (present and within specifications 99.999% of the time.) For the engineers who must manage the dispatch of generation, the reserves and the transmission constraints of the grid, grid-tied solar energy presents no problem as long as its contribution is a small percentage of the energy flowing through the system. For traders in deregulated wholesale energy markets who resell energy to end users, and who must anticipate their customer's demand, solar energy generation that is distributed amongst those customers presents no problem, again, so long as that generation makes up only a small percentage of the total demand. If solar energy generation systems rise to meet a more significant fraction of the daytime energy demand of the electrical grid, methods will need to be developed to accurately predict their contribution. Those predictive methods will necessarily function on the same hourly basis as is used to dispatch traditional generating resources. These same considerations apply to energy markets. If solar energy generation systems become a major contributor to the total energy mix within an operating territory they could be potentially disruptive to the wholesale electrical energy market unless their contribution can be accurately predicted within the same timeframe as that market.

2. DEREGULATED ELECTRICITY MARKETS

The movement to introduce competition into electricity markets has resulted in a plethora of differing forms and degrees of deregulation of the vertically integrated utilities that were once regulated monopolies. In its simplest form, utility deregulation seeks to separate the generation, transmission, and distribution functions of the electricity industry and allow companies to compete in the first arena – generation-- while retaining the later two as regulated enterprises. This process allows electrical energy to be traded in much the same way as other commodities. There are, however, several characteristics of electricity that make it unlike any other commodity, the foremost of which is the fact that, with very few exceptions, electricity cannot be stored in bulk. Electricity must be used as soon as it is created. For this and other reasons the generation and delivery of electrical energy must be closely managed, on an hour by hour –even second by second— basis. This peculiar characteristic of the technology has the ramification that, for many forms of restructured electricity markets, the electrical system operator that manages the physical distribution of electricity also manages its commodity market. Further, because demand cannot be precisely anticipated in advance, the timing of electricity markets is structured both on a long-term basis (forward contracts made months in advance of delivery) and on a short-term basis (day-ahead or hour-ahead of the delivery).

This study focuses on the day-ahead market. While over 80 percent of transactions in most deregulated markets are made in forward contracts [1], a portion of the purchases and sales must be made either in a day-ahead or spot market. As a point of reference this study takes as its context the daily trading schedule of the day-ahead market for the New England Regional Transmission Organization (New England RTO, formerly New England Independent System Operators or ISO New England). The trading practices employed here are an example of the Federal Energy Regulatory Commission's (FERC's) Standard Market Design (SMD). Specifically, the forecast of photovoltaic energy production will be timed to be available for the day-ahead bid deadline of 12 noon for the period starting at midnight that day and continuing until 11: 59:59 the following day [2].

3. DAY-AHEAD FORECASTING PV PRODUCTION

3.1 PV Production Forecast Methodology

A nominal 2 kWac (2.28 kW STC) photovoltaic system located in Northborough, Massachusetts, was surveyed and the characteristics of its array tilt and azimuth angles, its inverter efficiency and its balance of system components were recorded. The AC energy output of the system was monitored using a utility revenue grade kilowatthour meter with a nominal accuracy of +/- 21W. The meter readings were recorded in 15-minute increments on a General Electric DR-87 data logger.

Forecast weather data for the site, in the form of percent cloud cover and temperature, were collected from the National Weather Services' National Digital Forecast Database (NDFD) [3]. These forecasts were collected each morning before noon (prior to the New England RTO deadline for bids in the day-ahead market for the following day). The NDFD three-hour records were interpolated linearly to one-hour intervals for cloud cover and temperature forecasts. The interpolated values were divided into nine "bins" corresponding roughly to cloud cover octa codes. The conversion from percentage cloud cover to N octa values was done using equation 1

$$N \text{ octa value} = \frac{\%cloud\ cover}{100} \times 8 \qquad (1)$$

(This formula resulted in a real number version of the octa number instead of an integer value.)

The Kansten-Czeplak cloud-cover radiation model (CRM) was used to first simulate global solar irradiance for a cloudless day (I_{Gc}) using equation 2 and location-specific coefficients for Massachusetts listed in table 1 [4].

$$I_{Gc} = (A \sin \alpha) - B \qquad (2)$$

where α = solar altitude.

TABLE 1: COEFFICIENTS FOR CRM

Location	*A*	*B*	*C*	*D*
Massachusetts	1098	63	0.75	3.4

Global horizontal irradiance (I_h) was then calculated using equation 3 from the CRM.

$$I_h = I_{Gc}(1 - C(N \div 8)^D) \qquad (3)$$

Diffuse horizontal (I_{dh}) was calculated using CRM equation 4.

$$I_{dh} = (0.3 + 0.7(N \div 8)^2) \times I_h \qquad (4)$$

This method was used to calculate values of forecast global horizontal (I_h) and forecast diffuse horizontal irradiance (I_{dh}) for each hour of each day. The beam irradiance on a horizontal surface (I_{bh}) was then obtained as the difference between global horizontal and diffuse horizontal using equation 5.

$$I_{bh} = I_h - I_{dh} \qquad (5)$$

Finally, direct normal irradiance (I_{bN}) was approximated from beam horizontal irradiance using equation 6.

$$I_{bN} = I_{bh} \div \sin \alpha \qquad (6)$$

where α = solar altitude for the hour in question [5].

The CRM model results included negative values for global horizontal, diffuse horizontal for nighttime hours. All of these hours were filtered and set to zero. The final forecast simulated irradiance data set was limited to the hours between 8:00 am and 4:00 pm for most of the data set.

The hourly forecast/simulated irradiance and temperature data were then used as inputs in a commercial PV simulation software program, PV Design-Pro [6]. The output of this program was a forecast simulation, on an hourly basis, of the AC power production of the PV system.

The forecast hourly output of photovoltaic production for the Northborough system was then compared with its measured production for the forecast days.

3.2 Forecast Simulation Results

On days forecast to be largely cloudless the power forecasting model worked very well. Figure 1 is a typical day with zero forecast cloud cover. There is a time difference of approximately one half of an hour between the forecast solar noon from the simulation and the time of solar noon seen in the measured PV power production. This may be due to an inaccuracy in the longitude or hour angle calculations in our input to the CRM model, and should be correctable.

There were at least seven days during the data collection period when there was significant snowfall. These days adversely affected the apparent performance of the model. At times, though the solar resource was either wholly or partly available, the array was covered in snow and the power production was nearly zero. After examining the data closely these days were discarded as outliers. This filtering was justified due to the reasoning that a user of this model would be aware of the effects of snowfall and would account for it by discounting these days.

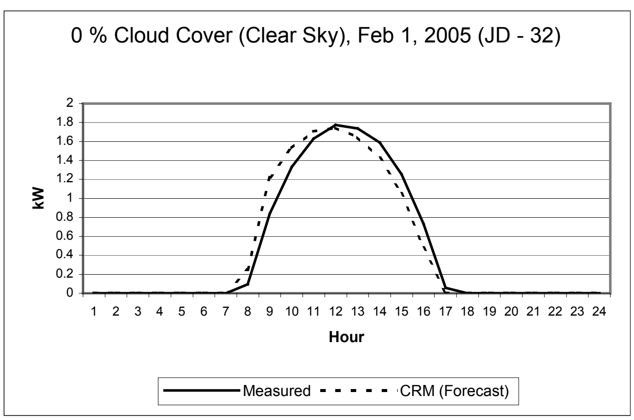

Fig. 1: Low cloud cover day with good match between forecast and measured PV production.

Figure 2 illustrates an overcast day with changing levels of irradiance. This example was selected from a pool of days that where the cloud cover forecast ranged from 40% to 90%.

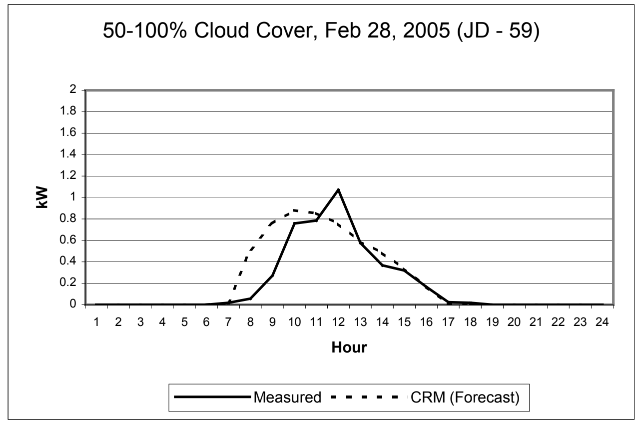

Fig. 2: Changing irradiance.

Figure 3 illustrates a day with very high cloud cover predicted.

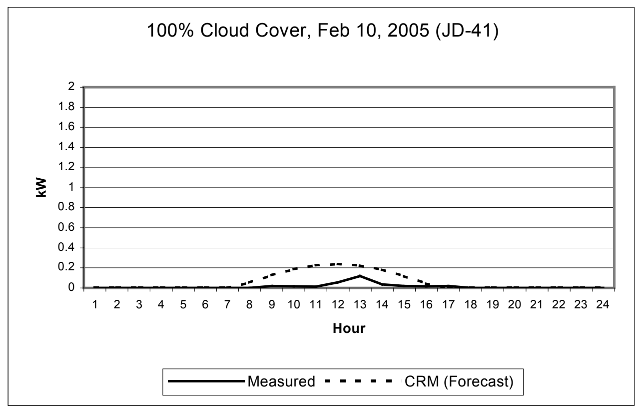

Fig. 3: 100% cloud cover predicted.

3.3 Error Analysis

To attempt to quantify the accuracy of the forecasting process the hourly data were grouped into ten bins, based upon forecast percentage cloud cover, in 10% increments (forecast cloud cover = 0-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-70%, 70-80%, 80-90%, 90-100%.) The data were filtered to remove nighttime hours. Each hourly forecast power value (P_f) and the corresponding measured power production for that hour (P_m), irrespective of the days in which they occurred, were placed in these bins (portions of the statistical analysis that follow are heavily derived from study thesis work of Elena Franzen [7]). The root mean square error (RMSE), expressed in kWac, was calculated for each bin for each hour of forecast and measured power values using equation 7.

$$RMSE = \left(\frac{1}{N}\sum_{1}^{N}(P_f - P_m)^2\right)^{1/2} \quad (7)$$

Figure 4 illustrates the RMSE for forecast and measured power by estimated cloud cover amount.

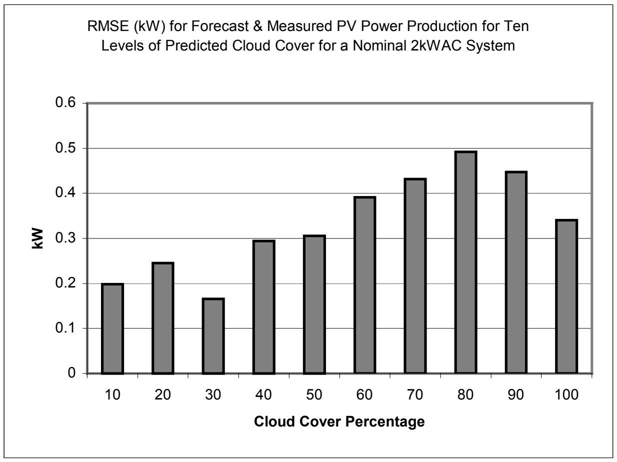

Fig. 4: RMSE of forecast and measured power for ten cloud cover ranges for a nominal 2kWac PV system.

The error in predictive accuracy increases for cloud cover levels between the 60% and 90%. These results indicate that the power production predictions made using this process are more reliable for those hour forecast to be either very clear and very cloudy. For the hours predicted to have 30% or less cloud cover the average RMSE was less than 10% of the rated power of the system. The RMS error in the predictions of system power for cloud cover forecasts for the range of 70% to 80% was as high as 25% of the full-scale output of the system.

4. TRADING PV ENERGY

For energy traders that have long-term energy contract obligations to serve loads, this method provides a means to anticipate the short-term demand of their customers who have solar generation capability within their facilities. The method adjusts the trader's short-term energy purchases or sales in a day-ahead market.[1] The energy trader would use this PV power forecasting model, in combination with a traditional load forecasting model, to estimate the net hourly energy consumption (or production) of his customers in the time period defined by the day-ahead market. This estimate is then subtracted from the long-term energy contract amounts, which the trader has purchased to meet his load obligations during the hours in question. The difference between the forecast hourly estimated demand (net production or consumption), and the energy amount that has been purchased under long-term agreements, can then be either sold as surplus or purchased to fill an anticipate shortfall.

5. DERIVITIVES AND ANCILLARY SERVICES

5.1 Hedging Day-Ahead Energy Sales

In addition to estimating the shortfall or surplus of traders' long-term forward contracts in the time period of the day-ahead markets, this process could be used to develop methods for insuring or hedging energy sales or purchases in the day-ahead markets against shortfalls in the spot market. An hourly day-ahead energy futures market could be organized which would consist of options to buy or sell blocks of energy in the spot market, at pre-agreed prices. Buyers and sellers of options in this market would use the performance history of the day-ahead net energy forecasts for regions with customers with solar generation capability within their facilities, in combination with estimates of the minimum and maximum spot market cost of energy, to assess the risk associated with purchases or sales of energy that are based upon those forecasts. Energy traders in the day-ahead market that buy energy because of an anticipated shortfall or sell energy because of an anticipated surplus in their long-term contracts would be able to purchase options to buy energy in the spot market at a pre-agreed price, in order to mitigate their exposure for shortfalls in the spot markets. They would purchase options based upon their assessment of the accuracy of the forecasting technology, in combination with their estimate of the cost of energy in the spot market and their tolerance for risk. This would create greater liquidity in the market by permitting a wider range of market participants.

5.2 Ancillary Services for PV

While aggregated photovoltaic attributes do not correspond to the types of ancillary services that are typically defined in electricity markets, such as various forms of operating reserves, it is possible to imagine attributes of PV that do contribute to the "common good" of the transmission and distribution systems which at present are not "captured" for PV owners whose systems are on the load side the revenue meter. For example, the thermal benefits of load reduction, if aggregated and associated with a particular location or zone, might be assessed and quantified, and their monetary value used to reduce the energy costs of the PV system owners. Other, more complex possibilities such as the VAR support may also be possible depending upon the state of inverter technology and the contractual arrangements between distribution companies and the PV system owners. Forecasting the availability of these aggregated attributes,

---

[1] It should be noted that a simplified version of the same process can be used to adjust purchases and sales in the spot market. And an even simpler subset of the process could be used for traditional regulated utilities whose customer base has significant PV capacity on the load side of their revenue meters.

with a known confidence level, could make them tradable commodities.

5. CONCLUSION & SUMMARY

Prediction of photovoltaic power production, based upon forecast meteorological parameters such as cloud cover and ambient temperature, can be achieved on an hourly basis, a day in advance. Further, it is possible to time this process to a market schedule such as that of the RTO New England day-ahead market, or any other day-ahead or hour-ahead market, using existing technology.

The forecasts of photovoltaic energy production done for this study were most accurate for days with very low cloud cover and very high cloud cover. We found that instances where snowfall was present caused a increase in the RMSE. These instances were eliminated as outliers. Our data set was forty three days, collected in the winter and early spring (1/30/05 to 3/13/05). To achieve a more accurate measure of the error that can be expected between the forecast and measured PV power it would be best to have an entire year of data.

All of the forecast simulations described in this paper were done for a single photovoltaic system. If the process were to be required on a regional scale, the model would likely be applied in the aggregate, as apposed to being computed one facility at a time. The information required as input to the simulation software could be collected either during the design phase of system installation, at the time of commissioning, or it could be surveyed after the system was operational.

6. ACKNOLWEDGEMENTS

The data used in this study were collected for an ongoing monitoring project conducted for National Grid USA Service Company, Inc. I would particularly like to thank Dr. John Bzura, PE, for his continued support in this area of research. I would like to acknowledge Christopher Lin and Vinay Ananthachar of New Energy Options, for their contributions to the data collection, processing and statistical analysis of forecast data, and for the invaluable feedback that they provided in our many discussions.

7. REFERENCES

1. S. Hunt, “Making Competition Work In Electricity”, John Wiley & Sons, 2002, p. 168.
2. New England Power Pool, FERC Electric Rate Schedule No. 7, Market Rule 1 –NEPOOL Standard Market Design, pg. 29.
3. National Weather Services’ National Digital Forecast Database http://www.weather.gov/ndfd/presentation.htm
4. T. Muneer, “Solar Radiation and Daylight Models”, Elsevier Butterworth Heinemann, 2004, pg. 81.
5. D. Goswami, F. Kreith, J. Kreider, “Principals of Solar Engineering”, Taylor Francis, 2000, pg. 45.
6. Maui Solar Energy Software Corporation http://www.mauisolarsoftware.com/
7. E. Franzen,” Development of a Tool for the day-ahead prediction of photovoltaic power output”, study thesis, University of Dortmund, Faculty of Electrical Engineering & Information Technology, Institute of Energy Systems and Energy Economics, EV 0418, 2004