NATURAL VARIABILITY OF IRRADIANCE AND POWER – SIMPLE VARIABILITY METRICS FOR PHOTOVOLTAIC POWER PLANTS

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ABSTRACT

Electric power utilities have the continual task of balancing the load with available generation. The load constantly changes in both predictable patterns (e.g. from seasonal and daily load variations), and in less predictable ways (e.g. the minute-to-minute variations or longer). The reserve and regulation activities required to balance these less predictable variations are called "ancillary services" which add to the overall cost of integration. One characteristic of solar photovoltaic (PV) power is that it varies over all the time scales of utility operations, and thus is expected to increase the ancillary services requirements. Presented here are two metrics that aid in assessing the impact of solar variability onto the grid: the Natural Variability of Irradiance (NVI) and the Natural Variability of Power (NVP). These metrics are statistical measures of changes in irradiance and power. The metrics will be defined and demonstrated using data from a 2.66-MW PV power plant.

1. INTRODUCTION

Solar photovoltaic (PV) power plants, classified as variable generation (VG) [1], can translate resource variability into both power and voltage variability within an electric utility's distribution system. This introduces a level of uncertainty to power generation that utilities will need to understand at higher solar PV penetration levels than previously observed. These higher penetration levels will require more ancillary services; particularly regulating reserves (spinning and non-spinning). Presented here is the development and implementation of a simple set of metrics that can help quantify that variability, from energy resource to energy production. The metrics, called here as the Natural Variability of Irradiance (NVI) and the Natural Variability of Power (NVP), do not require a site specific clear sky index to be generated. As such, these metrics are easy to use and are applicable throughout the entire time series in question. Knowledge gained from the use of these metrics could aid in the decrease of integration costs through ancillary services.

In June of 2010, the Sustainable Energy Solutions Group (now the Institute for Sustainable Energy Solutions) at Northern Arizona University (NAU) was awarded a contract working with Arizona Public Service (APS) in order to explore the inherent output variability from 2.66 MW of solar PV installed at the Prescott Airport PV Power Plant [2]. During this contract, it became evident that metrics needed to be generated that were (1) simple to generate from a given dataset and (2) easy to digest. The desired results for this metric (or set of metrics) were simple: to quantify the high temporal variability of the solar resource, to quantify the high temporal variability of the power output from a power plant given that resource, and then to quantify the smoothing of the variability from resource to power plant output.

2. NATURAL VARIABILITY OF IRRADIANCE AND POWER

In searching for a statistical means to represent the variability, analogous metrics from other industries were evaluated. One of those metrics found was the Turbulence Intensity (TI) metric used in the wind energy industry to quantify wind resource turbulence. TI is defined by the standard deviation of the wind speed divided by the mean of the wind speed [3]:

$$TI = \frac{\sigma_U}{\bar{U}} \tag{1}$$

where σ_U is the standard deviation of the wind speed sample:

$$\sigma_U = \sqrt{\frac{1}{N_s - 1}\sum_{i=1}^{N_s}(U_i - \bar{U})^2} \tag{2}$$

Typically, wind data is collected at 1-2 second intervals and TI (along with other statistical representations of the data) is calculated for 10 minute time periods. Note, even though wind data can be represented as a Weibull probability density function (PDF) through time (e.g., for an entire year's worth of data), in relatively small timescales (e.g., across 10 minute time periods) the turbulent wind data can be assumed to be Gaussian [3]. This shows the statistical relevance of TI as a metric for highly turbulent flow in small time scales (which coincide with the times of greatest need for such a metric).

Solar irradiance data can be viewed with very different PDFs (such as a Beta PDF) than wind energy across both large and small timescales. Typically, the application of a statistical moment, like standard deviation, to these PDFs (such as the distribution of typical solar irradiance) reduces its statistical relevance. This is due to the wavelets observed in the irradiance data that are characteristic of a cloud passing over, which causes variability. These wavelets predominantly decrease the resource, negatively skewing the distribution from the mean. So, in order to generate a simple metric using some of the lower-order statistical moments, the irradiance needs to be represented in a different manner; particularly one in which the standard deviation has statistical relevance in variable conditions.

To do this, and to capture the variability with the metric, the changes in irradiance from one time step to the next were considered. These "changes in irradiance" have a symmetrical distribution and, in small timescales, approach Gaussian in highly variable conditions. With this assumption, taking the standard deviation of the changes in irradiance has statistical relevance.

In order to compare the resource variability with other variability (such as power, voltage, or even another resource), it was determined that the metric should be normalized into a non-dimensional form. Some values were considered: 1000 W/m^2, the maximum of the sample irradiance, the mean of the sample irradiance, and the clear sky index (CSI). Due to the arbitrary nature of using 1000 W/m^2 when considering sites at various geographic elevations, this value was not used. And because the irradiance in a day could be observed to be low nominally but have a short period of high irradiance, the maximum of the sample irradiance was also not used. Potential inaccuracies of the clear sky model in generating an accurate CSI throughout all hours of a given day (without further on-site measurements besides the global horizontal irradiance or the use of modeling techniques) and a desire for a simpler metric led to the decision not to use a CSI to normalize the metric (though CSI is used in other metrics [4-5]). Finally, the mean of the sample irradiance was considered and found to be a good representation of the data for the purpose of normalizing the metric.

For ease of use, this metric was given a name: the Natural Variability of Irradiance (NVI), which is defined here as the standard deviation of the changes in the irradiance sample divided by the mean of the irradiance sample:

$$\boxed{NVI = \frac{\sigma_{\Delta G}}{\bar{G}}} \tag{3}$$

For comparison, other metrics can now be defined in a similar manner. An example is the Natural Variability of Power (NVP), defined here as the standard deviation of the changes in the power sample divided by the mean of the power sample:

$$\boxed{NVP = \frac{\sigma_{\Delta P}}{\bar{P}}} \tag{4}$$

Further metrics could be defined in a similar manner such as individual inverter power or even voltage, but NVI and NVP will only be explored here.

3. A SIMPLE IMPLEMENTATION OF THE METRIC

Now that the NVI metric (and possible suite of other metrics) has been developed and defined, a simple example should be given for implementation. Similar to the use of TI in the wind industry, solar data can be collected at 1-2 second intervals (preferably one-second) and NVI can be calculated for ten-minute time periods. For example, if a ten-minute mean of irradiance data collected at one-second intervals is 500 W/m^2 and the standard deviation of the one-second changes of irradiance is 50 W/m^2 for that ten-minute sample, then the NVI over that ten-minute sample is 0.1. This "ten-minute NVI" example can then be used across an entire dataset. An example of the implementation of the ten-minute NVI can be seen in Figure 1, which shows four different days of global horizontal irradiance (GHI) in the top subplot (collected at one-second intervals) along with the corresponding ten-minute NVI in the lower subplot.

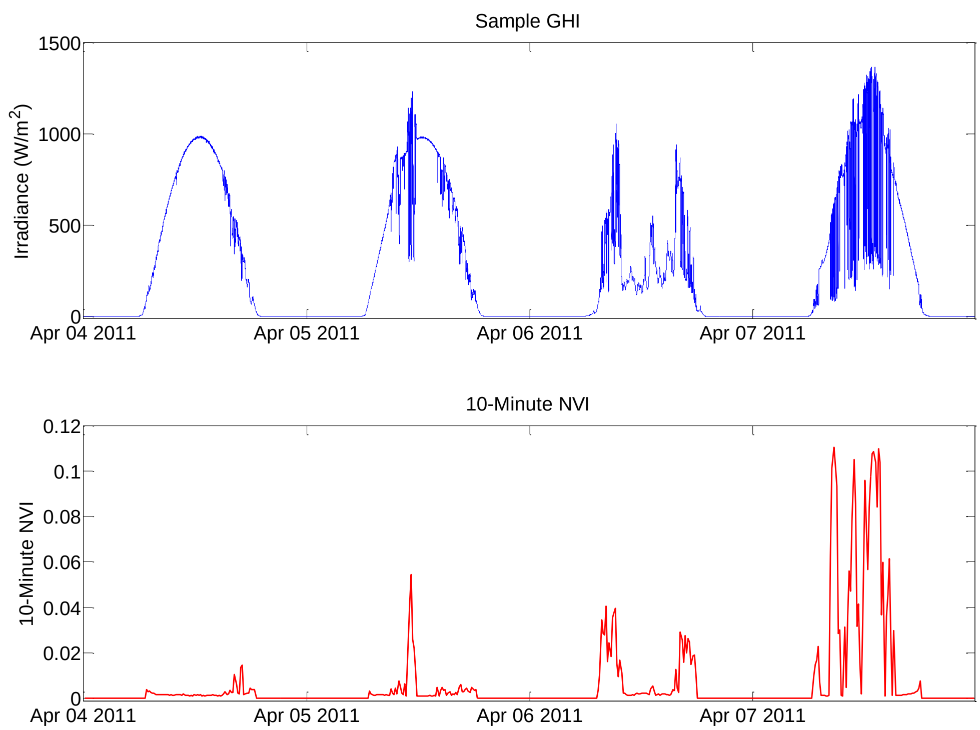

Fig. 1: Top Subplot: Sample 1-Second Global Horizontal Irradiance (GHI) for April 4, 2011 to April 7, 2011 at the Arizona Public Service (APS) Prescott Airport PV Power Plant. Bottom Subplot: Corresponding Ten-Minute Natural Variability of Irradiance (NVI) for April 4, 2011 to April 7, 2011.

4. THE NVI CLASSIFICATION SYSTEM

Now that it can be seen that the NVI metric can quantify variability in a simple and easily digestible way, a classification system can be proposed. This classification system can be used to classify samples of irradiance (e.g., ten-minute, hourly, or even daily NVI). One such classification system can be seen in Table 1. In this classification system, a Class 1 sample has low variability and a Class 7 sample has high variability. Note: this process could also be carried out to classify power variability resulting in a NVP classification system.

TABLE 1: A Sample NVI Classification System

Class 1 NVI	<0.005
Class 2 NVI	0.005-0.01
Class 3 NVI	0.01-0.025
Class 4 NVI	0.025-0.05
Class 5 NVI	0.05-0.1
Class 6 NVI	0.1-0.2
Class 7 NVI	>=0.2

Using this classification system (or a similar one), irradiance samples can be classified to gain further insight into the data. The data can be classified in ten-minute samples (as suggested in the ten-minute NVI sample above) or even in daily samples. Figure 2 shows some sample days of GHI categorized using daily NVI values for each of the first 6 classes in table 1. And Figure 3 shows the GHI values from Figure 1 now coded with this NVI classification system using ten-minute sampling to calculate NVI.

This classification system is not, and should not be, limited to what is suggested here. Instead, the classification system presented should be considered an example and a good starting point. Furthermore, it should be noted that because the perceived variability changes with the temporal resolution to which it is measured, the classification system is completely dependent on that temporal resolution of the data collected.

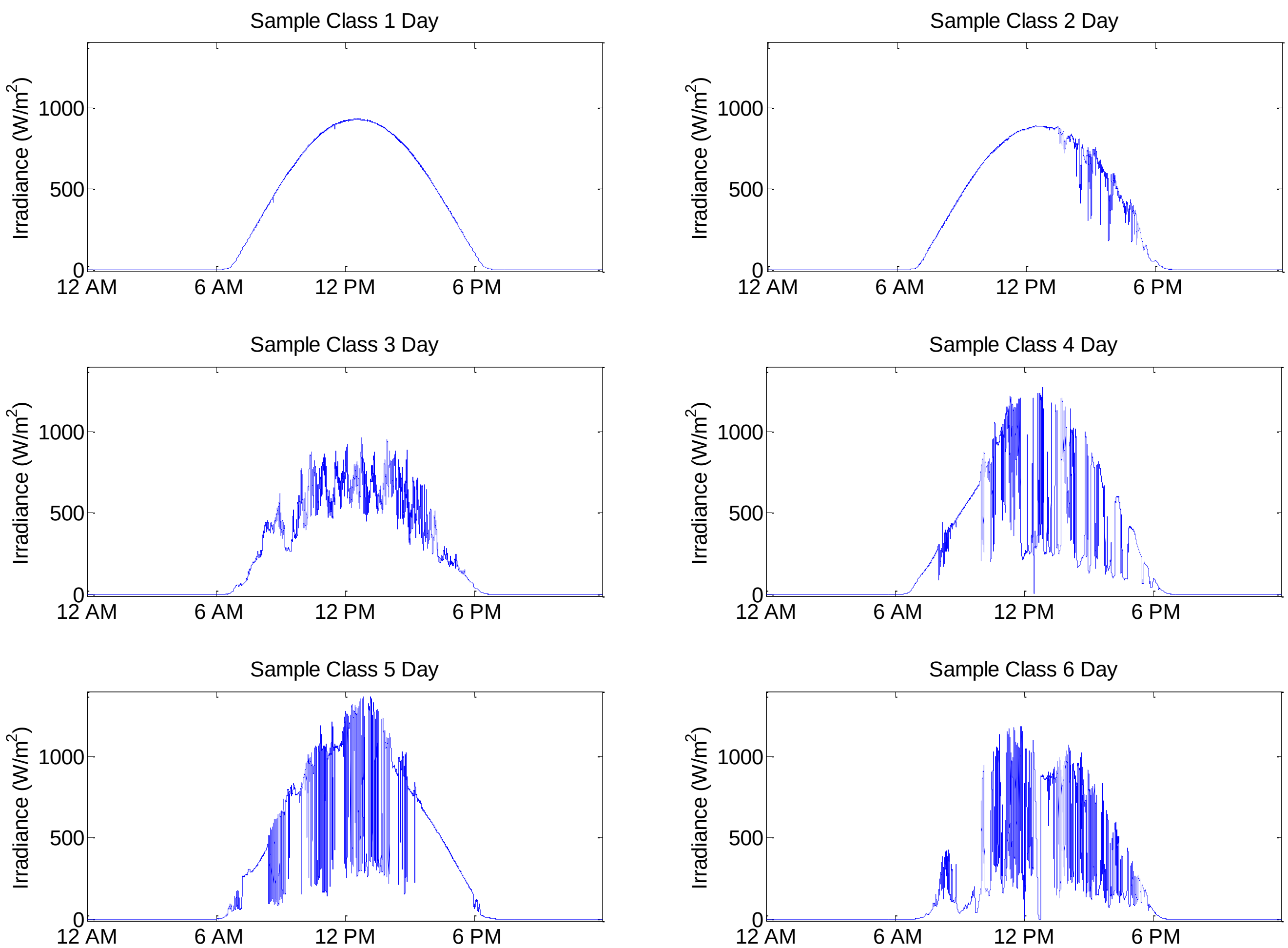

Fig. 2: Sample Days of Global Horizontal Irradiance (GHI) for daily Natural Variability of Irradiance (NVI) classes 1-6 from Table 1. These sample days were collected from the Arizona Public Service (APS) Prescott Airport PV Power Plant during the months of March and April of 2011.

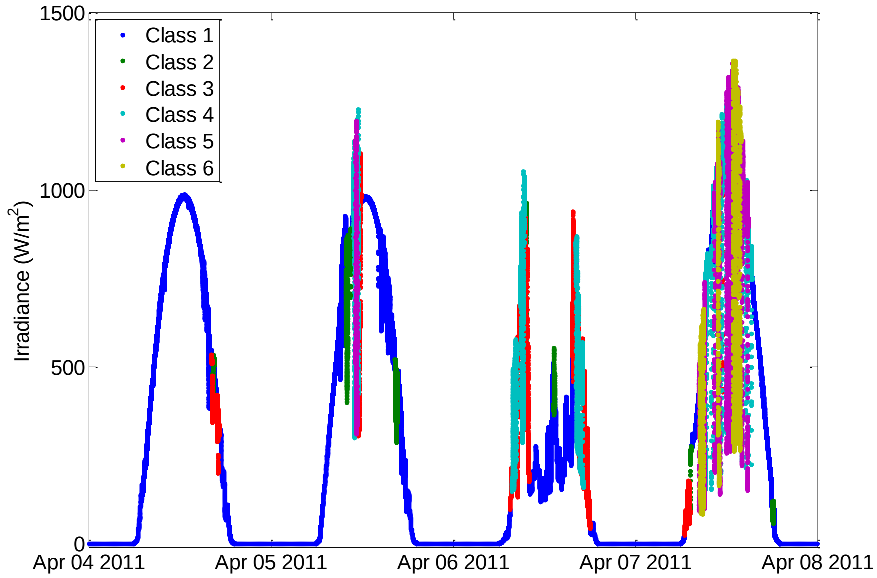

Fig. 3: Global Horizontal Irradiance (GHI) Coded with Natural Variability of Irradiance (NVI) Classes for Ten-Minute Samples for April 4, 2011 to April 7, 2011 at the Arizona Public Service (APS) Prescott Airport PV Power Plant.

5. THE NVI/NVP RELATIONSHIP

The smoothing observed across the spatial domain of a PV power plant can be quantified by comparing the values calculated for NVI and NVP. Figure 4 shows this smoothing of the variability during an example month at the Prescott Airport PV Power Plant.

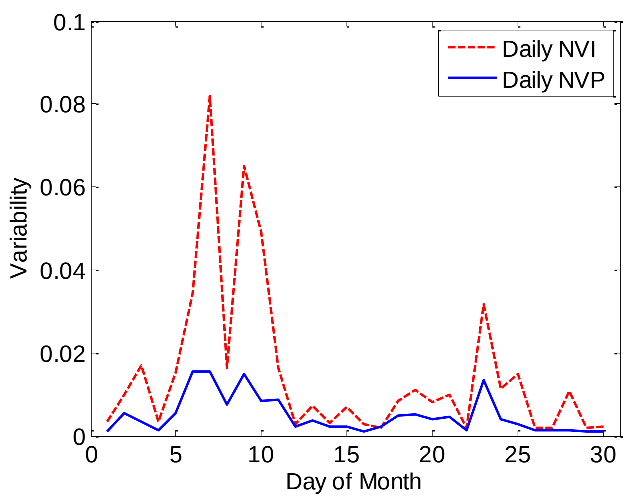

Fig. 4: Resource smoothing as observed from the Natural Variability of Irradiance (NVI) and the Natural Variability of Power (NVP) during the month of April, 2011 at the Prescott Airport PV Power Plant.

Because a single irradiance station is a point measurement, it does not quantify exactly what was observed across the entire spatial range of a given plant. Hence, the power output of the plant is less variable than the resource observed at that irradiance sensor. This Variability Reduction (VR) of a sample can be expressed as the ratio of the two metrics for that sample in time:

$$VR = \frac{NVI}{NVP} \tag{5}$$

Another way of looking at the variability reduction of a PV power plant is by using the NVI and NVP metrics and expressing them in terms of installed capacity. To do this, the data from the APS Prescott PV Power Plant was first binned with respect to its variability and installed capacity. In order to gain insight into the relationship between NVI, NVP, and installed capacity, the 2.66 MW plant was analyzed as an aggregate of some and all inverters on site. This aggregate approach provided the analysis with multiple data points that were binned in order to find a trend. This three-dimensional trend (or surface trend) was then found through the average of those bins. From this procedure, an empirically derived NVI/NVP/Power relationship from the data can be expressed in terms of NVP for any power block size (or combination of power blocks) between 0.2-2.7 MW (the range of the combination of inverters at this APS site):

if NVI <=0.1:

$$NVP = P^{-0.471}[-3.1093(NVI)^2 + 0.7827(NVI)] \quad (6)$$

if NVI>0.1:

$$NVP = P^{-0.471}[0.082(NVI) + 0.0394] \quad (7)$$

where P is installed capacity in MW.

Figure 5 shows equations (6) and (7) graphically for 200, 700, 1200, 1700, 2200, and 2700 kW of installed capacity. As expected, the larger the installed capacity of a PV power plant, the more of a reduction in this high temporal resolution variability is observed.

Of note, from these equations, is the exponential reduction in that variability with respect to installed capacity. This same procedure can be performed on other power plants, regardless of installed capacity, and a similar relationship can be found. Different relationships could be found depending on power plant size, orientation, site fill factor, tracking configuration, and plant aspect ratio with respect to cloud travel.

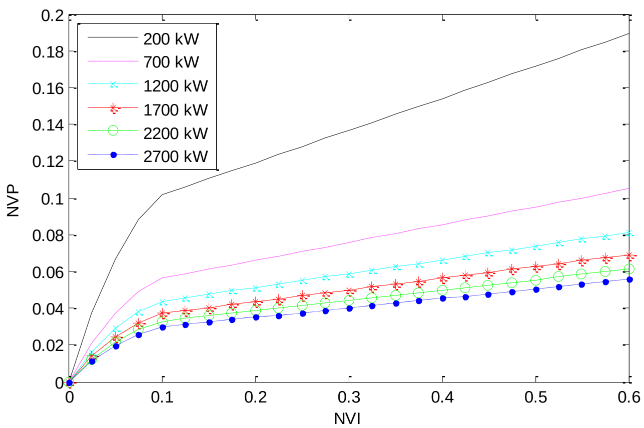

Fig. 5: The relationship between Natural Variability of Irradiance (NVI), Natural Variability of Power (NVP), and Installed Capacity (~0.2-2.7MW). This relationship could be viewed with a surface plot, but is viewed here as a line plot for simplicity.

6. NVI, NVP, AND FORECASTING RESERVES

NVI and NVP could be used in the future to aid in forecasting reserve needs on a particular load. Historical data could be used to tie weather data to power output variability using the NVI and NVP metrics. To do this, NVI could be directly tied to cloud types giving a relationship between clouds and the resource variability that they generate. Once there is a link between cloud type and NVI, then there is a direct link between cloud type and NVP. This could be done using a cloud classification system and a NVP classification system that are directly mapped to each other.

This cloud to power variability knowledge could be imbedded into a solar power forecast alongside the given load forecast and be applied to the day ahead, which could give more accuracy to how next day reserves get planned to anticipate the expected power variability. As experience is gained on the correlation between changing forecasts hour to hour and the resultant NVP, hourly adjustments could be make on the reserves (similar to how load forecasting is used). By having this relationship already embedded into the forecast, the knowledge will be there to make better informed decisions on reserve needs which will reduce the cost of solar PV integration.

7. CONCLUSIONS

While analyzing the 2.66MW Arizona Public Service (APS) Prescott Airport PV Power Plant, a simple set of metrics was devised in order to quantify the high temporal resolution variability observed across a PV power plant. The Natural Variability of Irradiance (NVI) was generated to capture the variability in the resource at a single point measurement (e.g., from a pyranometer). Then the Natural Variability of Power (NVP) was generated to quantify the power output variability from a solar PV power plant. And finally, the variability smoothing was defined with Variability Reduction (VR) as well as the NVI/NVP/Power relationship and forecasting reserves were commented on. These simple tools can be implemented when an understanding of the high temporal resolution variability is desired. It can also be conceived that these metrics be used in both the modeling of PV power plants as well as in the forecasting for those PV power plants. These applications can inform utilities and operators as solar PV penetration increases and aid the deployment of ancillary services.

8. ACKNOWLEDGEMENT

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