Effects of Solar Resource Variability on the Future Florida Transmission and Distribution System

David K. Click, *Member, IEEE*, Houtan Moaveni, Kristopher O. Davis, *Member, IEEE*, Richard H. Meeker, Jr., PE, *Senior Member, IEEE*, Robert M. Reedy, PE, *Member, IEEE*, Anthony Pappalardo, and Rodica Krueger, *Member, IEEE*

***Abstract*—A common critique of photovoltaic energy is the susceptibility of the systems to high variability-- passing clouds can affect a site's day-to-day energy production substantially. This research developed a tool to simulate photovoltaic energy systems in several scenarios throughout the state of Florida and quantifies the hour-to-hour impact of these systems on the statewide generation mix using 11 years of historical weather data. While the hourly changes in aggregate system output for distributed PV systems was predictable between months, finer geographic granularity of irradiance data coupled with sub-hourly time intervals are required to further develop this model into one that is indispensable for utility system operators.**

***Index Terms*—Forecasting, interconnected power systems, photovoltaic power systems, power generation planning, and power system meteorological factors.**

I. Nomenclature

POA: irradiance incident upon the plane of a PV array
PV: photovoltaic energy source
GHI: global horizontal irradiance: diffuse plus direct irradiance incident upon a horizontal plane
ETR-GHI: extraterrestrial GHI
K: clearness index (GHI divided by ETR-GHI).
STC: Standard Test Conditions, at which a PV system nameplate capacity is calculated—1000 Wm^{-2} irradiance, 25 °C ambient temperature, 1 ms^{-1} wind speed.

II. Introduction

DRIVEN by concerns about climate change and long term energy security, including reducing reliance upon fossil fuels, it is evident that photovoltaic (PV) power sources will be part of the solution in supplying an increasingly energy-intensive world. Despite recent economic woes, solar PV has been one of the fastest growing industries in the world, with global PV module production capacity more than doubling in 2010 to 23.5 GW [1] and continuous market growth for over 30 years [2]. Currently, PV produces less than 0.02% of the overall electrical energy used in the United States—in 2010, 3.48 TWh of a total 22,200 TWh [3]—but the market has maintained a 40% annual growth rate in spite of the recent global economic downturn [1]. Increasingly high levels of PV penetration on distribution feeders, and, eventually even in localized parts of the transmission system, drives the need for a more thorough understanding of the intermittent nature of the PV power output and the collective impact of grid-connected PV systems on the electric power system.

In addition to traditional market barriers (e.g. cost, policy), there still exist technical challenges that will need to be overcome in the coming years to allow PV to be successfully integrated into power grid operations. One of these challenges is the uncertainty regarding the impact of very high penetration of PV on power systems, particularly arising from the intermittent nature of the resource. Because the PV generation is connected to the power system through power electronics, changes can be passed on very quickly to the grid, yet, with a great degree of control and protection. The North American Electric Reliability Corporation (NERC) anticipates PV output changes of ±70% in time frames of two to ten minutes, and suggests that PV plants have the ability to manage ramp rates and/or curtail their own power output [4]. Moreover, NERC enforces system operators to maintain a balance between generation and load as well as scheduled imports and exports across transmission systems. Currently, this means that dispatchable conventional generation is held in reserve to respond to rapid fluctuations in PV systems. This must also be taken into account in resource adequacy planning. Increased understanding of the variable nature of the resource can allow generation and transmission planning, accounting for variable generation sources that minimize investment in standby and reserve generating assets while maintaining system reliability.

There is also a need to more thoroughly understand the effects of high-penetration PV at the distribution system level, such as voltage regulation and reverse power flows, protection coordination, low frequency "flicker" (voltage swings) from passing clouds that can impact lighting and industrial motor loads, and island detection and islanded operation. This begins with detailed analysis and understanding of PV output variation for different time scales (from seconds to days). Numerous studies have been conducted on PV resource variability and high penetration PV effects in the Western

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D. K. Click, H. Moaveni, K. Davis, R. Reedy, C. Cromer, A. Pappalardo, and R. Krueger are with the Florida Solar Energy Center (FSEC) of the University of Central Florida, Cocoa, FL 32922 USA.

R. H. Meeker is with the Center for Advanced Power Systems (CAPS) at Florida State University, Tallahassee, FL 32310 USA.

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region of the U.S. This paper examines PV generation deployment scenarios in Florida and characterizes hourly PV system output profiles for historical periods to support analysis on impacts to the power grid caused by increasingly greater levels of PV penetration.

The 2011 peak load forecast for Florida is 47,613 MW, supplied mostly by fossil generation and about 10% nuclear. Florida is among 18 U.S. states without a renewable portfolio standard (RPS) and, in 2010, derived 1.2% of its net energy generation from renewable energy, mostly biomass and municipal solid waste, with solar less than 0.04%, though increasing steadily. Florida is mostly a peninsula with power import/export available only to the North. Reserve margins in Florida are maintained above 20% [5]. The largest operating grid-connected PV system in the U.S., the DeSoto Next Generation Solar Energy Center, is connected to the Florida transmission grid, with a 25MW capacity, however, due to the small size relative to transmission capacity and the location of the connection, the variability of this source has little effect on the Florida grid. Yet, if an RPS or similar incentives and policies producing a more favorable environment for renewable energy pass in Florida, solar PV generation growth at the distribution and transmission grid levels will increase significantly, as will the urgency of understanding high penetration effects in the Florida grid.

III. Methodology

As a first step to study high penetration PV, the expected PV output characterization needs to be determined. A PV simulation model tool, shown in Fig. 1 below, was developed to evaluate high penetration PV scenarios in Florida using an industry-standard performance model.

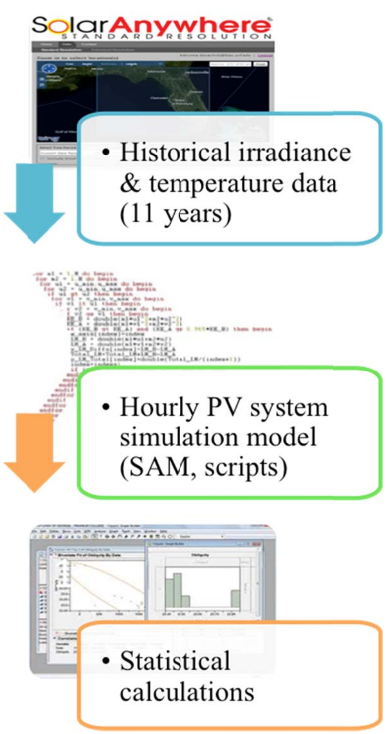

Fig. 1. The team's approach to modeling statewide power output for simulated PV systems.

The tool simulates PV performance for a single system individually as well as a fleet of different systems distributed across a region. The hourly solar irradiance information was downloaded from the SolarAnywhere web service, which derives this data from satellite imagery at a resolution of 10km x 10km [6]. Clean Power Research, the developer of SolarAnywhere, made eleven years (1998-2008 inclusive) of irradiance and terrestrial meteorological data within Florida available for this research. To translate the solar irradiance data into estimated power output for systems throughout the state of Florida, the team used the System Advisor Model (SAM) developed by the National Renewable Energy Laboratory (NREL). For this study, the PVWatts performance model, a simplified version of the Sandia performance model, was used within SAM to calculate hourly average power outputs of the PV systems. SAM estimates the incident irradiance and operating temperature of the PV modules themselves in order to accurately model PV power output. The team produced scripts to create test cases and automatically process the resulting datasets, to prepare them for further statistical analysis.

A. Output Variability

The PV system output changes proportionally with irradiance over time in the plane of the array (POA). These changes in intensity of the solar recourse over a given timescale are defined as PV output variability. Output variability is due to both the longer term deterministic changes associated with the diurnal solar cycle and seasonal changes, and more importantly in the context of predictability and forecasting, the short-term stochastic changes due primarily to clouds and other transient factors affecting the propagation of light through earth's atmosphere [7]. This output variability can be considered for a single PV system as well as an aggregate of multiple PV systems. The PV output variability is a calculated distribution of either irradiance or power step changes over a fixed time interval. The average PV output variability for a single system ($\sigma^{\tau}_{\Delta P_1}$) is defined in (1) as the standard deviation of the step changes over a different timescale period [8].

$$\sigma^{\tau}_{\Delta P_1} = \sqrt{\mathrm{Var}\left[\frac{1}{\tau}\sum_{i=0}^{\tau-1} P_1\,(t+i)\right] - \left[\frac{1}{\tau}\sum_{i=-\tau}^{-1} P_1\,(t+i)\right]} \qquad (1)$$

Where $\boldsymbol{\tau}$ is the duration of the averaging interval and t is the time interval.

The variability of an aggregation of multiple PV systems, $\sigma^{\tau}_{\Delta P}$, is defined in (2) [8].

$$\sigma^{\tau}_{\Delta P} = \sqrt{\left[\sum_{i=1}^{N}\sum_{j=1}^{N} \mathrm{Cov}(\Delta P_i^{\tau}, \Delta P_j^{\tau})\right]} \qquad (2)$$

Where N is the number of PV systems located across a balancing area or region.

B. Clearness Index

The clearness index (K) is a measure of how the actual irradiance for a given period of time deviates from the irradiance for a perfectly clear day. This provides a means of isolating the short-term stochastic changes in irradiance (i.e. the unpredictable changes) from the deterministic changes that can be determined analytically [9]. This provides a means of evaluating the predictability of the solar resource for individual sites as well as an aggregate of many sites. The equation for the clearness index is given by the following [7]:

$$K(t) = \frac{E_{GHI}(t)}{E_{ETR-GHI}(t)} \quad (3)$$

Where $E_{GHI}(t)$ is the global horizontal irradiance (GHI) at 0° tilt as a function of time, and $E_{ETR\text{-}GHI}(t)$ is the extraterrestrial GHI versus time. In this study, $E_{GHI}(t)$ was determined from the hourly SolarAnywhere data set and $E_{ETR\text{-}GHI}(t)$ was determined using a online tool created by NREL called the Solar Position and Intensity Calculator.

C. Spatial Correlation

It is well known that to mitigate variability, systems should be geographically dispersed (i.e. the so-called "smoothing effect") [10]. Short-term localized variations average over larger geographical areas, resulting in ramp rates for aggregated systems normally less than those of the individual systems. The correlation of system variability for multiple sites as a function of the distance can therefore quantify this effect. Pearson correlation coefficients were calculated for the clearness index of multiple sites using the statistical software package JMP. These coefficients give a quantitative measure of how effective multiple sites will be at mitigating variability for the group as a whole (i.e. well correlated output variability between multiple systems will do little mitigate variability). The ramp rates of the clearness index, $\Delta K(t)$, were used in this case, as opposed to GHI or modeled PV power output, to isolate the known correlation due to the aforementioned deterministic changes in irradiance due to the diurnal and seasonal solar cycle. In each case, this analysis was carried out over the 11 year period between 1998-2008. These correlation coefficients were investigated for sites distributed across Florida to assess the effect of distance between sites and variability correlation.

IV. Scenarios

In order to obtain a good examination of PV output variability, PV systems with differing tilt and orientation were selected, along with appropriate solar irradiance information for respective locations across Florida. In this study, three high penetration scenarios were developed to investigate variability and high penetration PV across Florida. The developed PV simulation analysis tool was used for testing build-out scenarios and providing some perspective relative to high PV penetration planning in Florida. In scenario 1, the simulation consisted of a 1kW PV system in each 10x10km grid in Florida, with each array sloped at the site's latitude and at an orientation of true south (a 180° heading). In scenario 2, the orientation of each PV system was set to a different, random direction facing generally south and between 90° (east) and 270° (west). In scenario 3, a statewide grid was modeled with distributed generation roughly located with and proportional to population density, with large ground-mounted PV power plants modeled in open areas. Table 1 describes the layout for each simulated square, while Fig. 2 shows the distribution of the squares throughout Florida. The total simulated capacity of approximately 75GW is within the technical potential for the state by 2020 [11].

Table 1
Description of grid squares modeled in Scenario 3.

Density	**MW per square**	**Orientation Notes**
Low-Density	20	20° slope, randomized orientation (90° - 270°)
Medium-Density	80	20° slope, randomized orientation (90° - 270°)
High-Density	160	20° slope, randomized orientation (90° - 270°)
Power Plants	400	50% of sites: 1-axis trackers 25% of sites: fixed at 20° slopes facing south 25% of sites: fixed at 20° slopes facing southwest

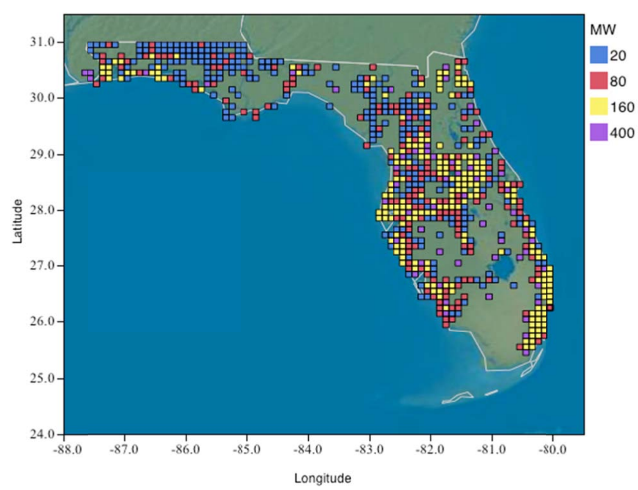

Fig. 2. Scenario 3 model, with approximately 75GW of capacity distributed statewide.

V. Results and Discussions

A. Temporal Variability

A south-facing PV system in Florida operating during a clear, sunny day would be expected to produce power throughout the day from dawn to dusk with a power output peaking in the middle of the day (when the sun is at its most normal angle to the array), with smooth increases and decreases in power output as the sun passed overhead. However, this rarely occurs in Florida, and Fig. 3 shows the effect of passing clouds on some partly sunny days in early June 2011.

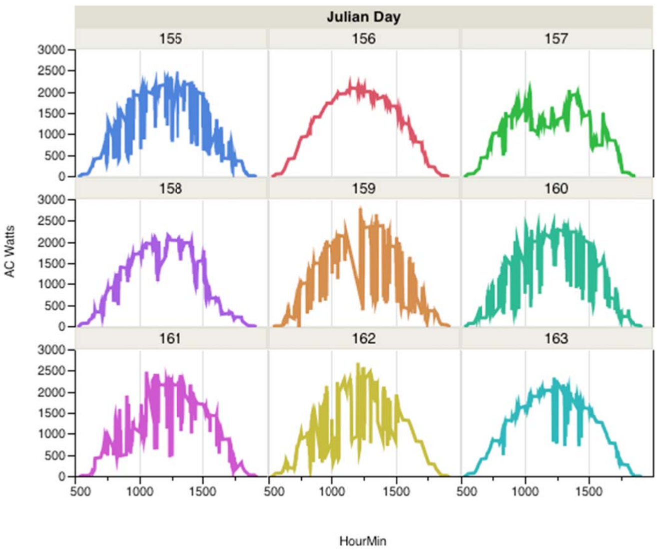

Fig. 3. Day-to-day variation of a 3kW PV system in Cocoa, Florida, using 0.25 second interval data.

As described earlier, mitigating this short-term variability can be done by dispersing PV over a large geographic area. Previous studies have shown that for N systems of equal size and with completely uncorrelated variability, the aggregated output variability can be reduced by the square root of N. The assumption of uncorrelated variability means the systems need to be sufficiently far apart. By calculating the correlation coefficients of six sites all across the state of Florida with respect to each other, a relationship between variability in the clearness index and distance emerged (Fig. 4). Only those systems located within 400 km of one another show a correlation over 0.05.

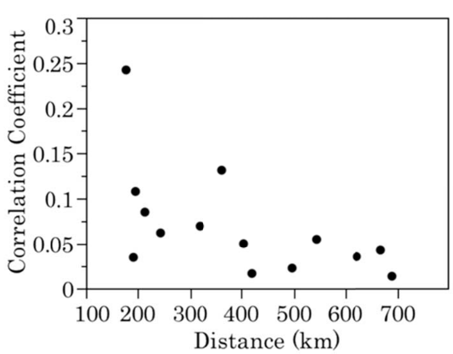

Fig. 4. Correlation of ΔK(t) versus distance performed on six sites with respect to each other.

Probability density functions were calculated for the individual sites as well as an aggregate of all six sites (taken by averaging K(t) over each site), shown in Fig. 5. The standard deviation of the aggregate site's distribution is clearly much smaller, as expected, resulting in a more predictable overall power output.

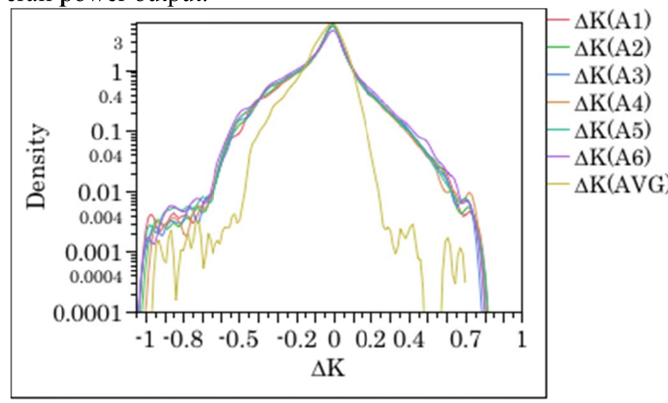

Fig. 5. Probability density function for the ramp rate of K(t) for each individual site and an aggregate of all sites combined.

When analyzing the statewide performance of these systems using the hourly data, the variability was consistent not only from hour to hour but also between months, as shown in Fig. 6 for the evenly-distributed statewide PV in Scenario 1. This figure depicts the average hourly changes in PV output as a changing percentage of the system's rated capacity.

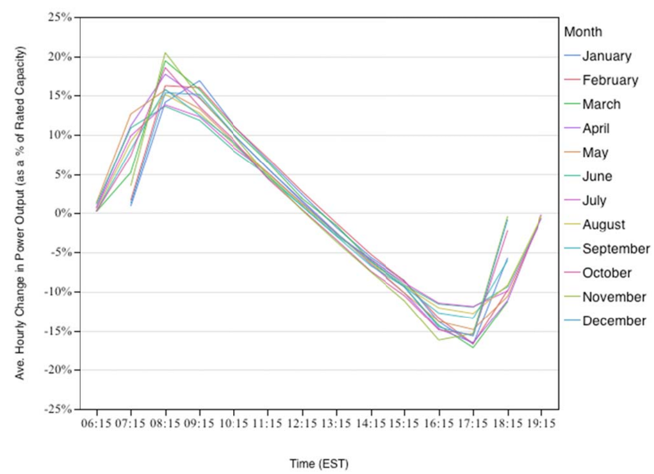

Fig. 6. Scenario 1, showing average hourly changes in power output (by month) as a percentage of rated capacity.

Average hourly changes in PV output were consistent between modeled scenarios as shown in Figs. 7-9. Each error bar is constructed using 1 standard deviation from the mean.

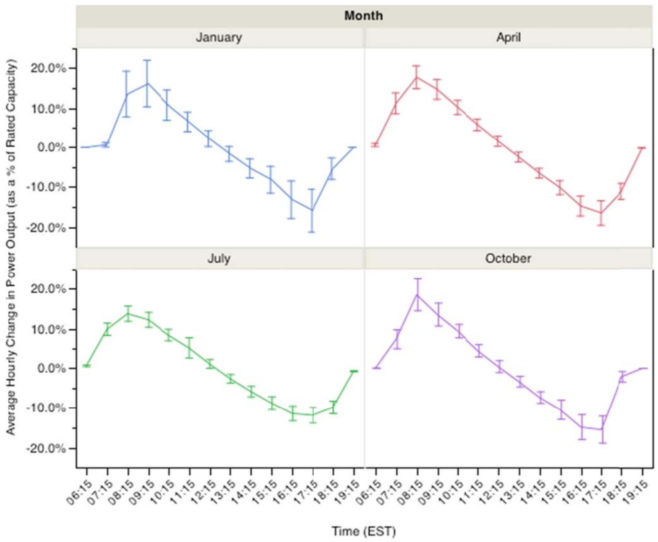

Fig. 7. Scenario 1: average hourly changes in PV output

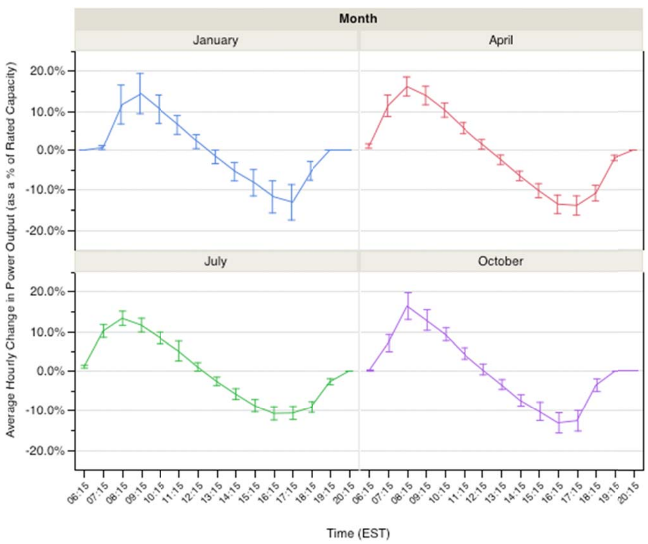

Fig. 8. Scenario 2: average hourly changes in power output

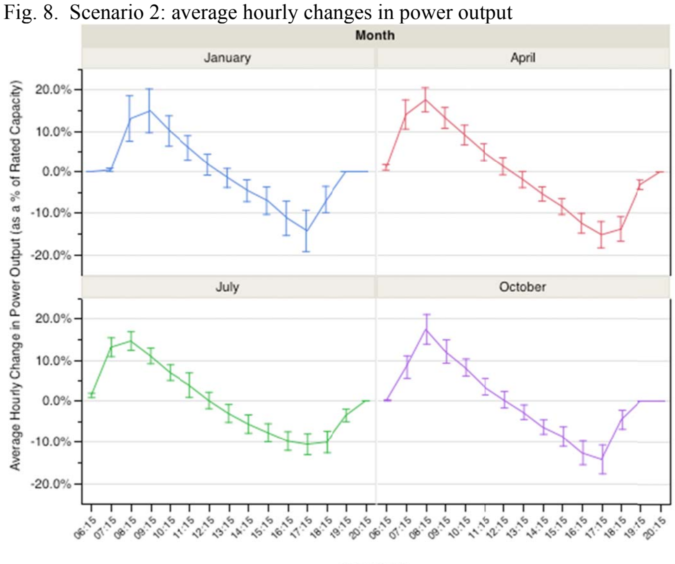

Fig. 9. Scenario 3: average hourly changes in power output

B. Variability of Small and Large PV systems

To illustrate the difference in variation between aggregated systems distributed across a wide geographic area and a single large system, Fig. 10 below shows hourly power changes over the first two years' operation of a 1MW PV system in Orlando, Florida. As the system production is distributed over thousands of square feet rather than thousands of square miles, the variability of this system is larger than that of the three scenarios.

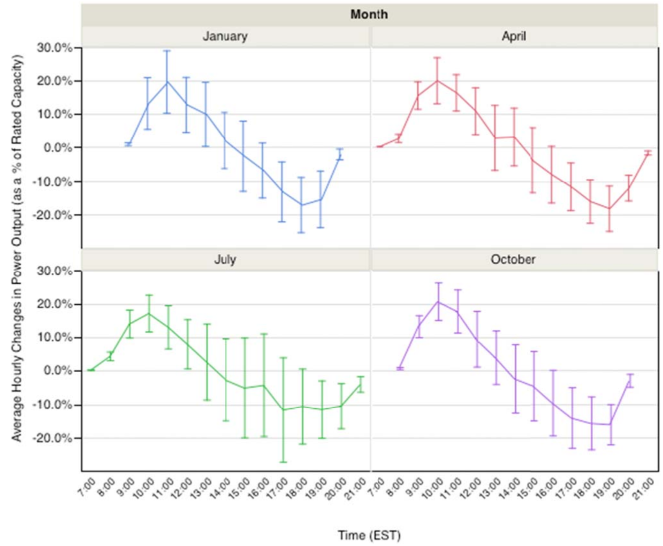

Fig. 10. Hourly changes in power production for a 1MW (1016kW) PV system in Orlando, Florida.

Variability was also verified to be greater for smaller systems. Fig. 11 depicts the different hourly ramp rates for a 3kW system in Cocoa, Florida during June 2011, compared with those for a 1016kW system in Orlando, Florida during the same period. The ramp rates for both systems fall generally between -25% to 25%, although as expected, the smaller system showed a wider range of variability than the larger, due to the aforementioned smoothing effects of a larger array area.

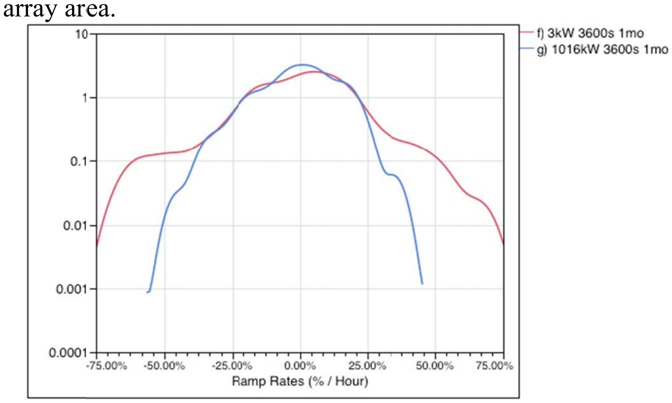

Fig. 11. Differing variability of 3kW and 1016kW systems, sampled hourly, as a % change in rated output per hour

Figs. 12-14 depict the ramp rates for the 3kW system, during the month of June 2011, when sampled at different time intervals. Shorter intervals have the expected lower ramp rates per interval; during just one second that month did the ramp rate per second exceed 25%.

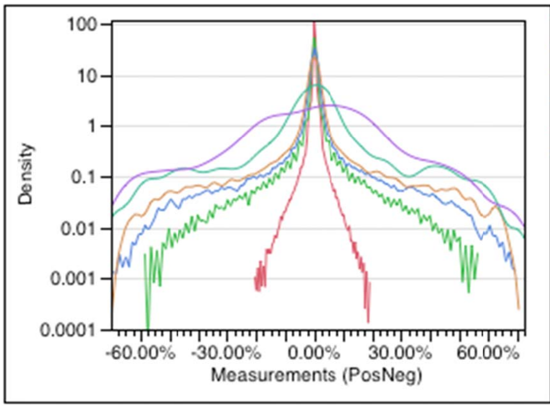

Fig. 12. Ramp rates for the 3kW system over 1s – 1hr time intervals, showing smaller ramp rates for smaller intervals.

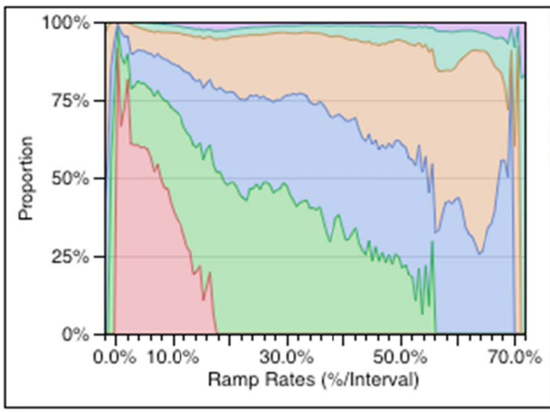

Fig. 13. Ramp rates for the 3kW system over 1s – 1hr time intervals, showing smaller ramp rates for smaller intervals.

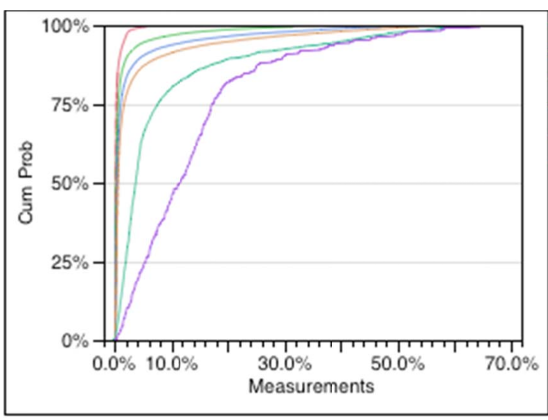

Fig. 14. Cumulative distribution function showing the probability of ramp rate magnitudes.

C. Spatial Variability

In addition to temporal variation, the team researched the impact of spatial variation on PV systems fielded in Florida, with the annual energy production in each grid square depicted in Fig. 15. This simulation (Scenario 1) featured identical PV systems in each grid square; as expected, systems further south had slightly higher yields than those in the north due to slightly more solar resource being available. However, it is unknown whether the coasts truly experience higher yields. Given that the yields on the coasts and within Lake Okeechobee are noticeably higher than in nearby grid squares, it appears that the SolarAnywhere models slightly exaggerate actual irradiance when analyzing grid squares that include water. This issue would be addressed with higher resolution spatial data, already available within SolarAnywhere for the state of California at a 1km resolution.

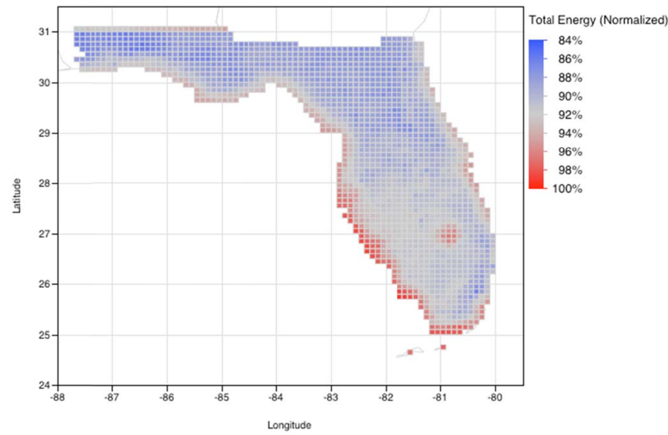

Fig. 15. Simulated energy distribution for evenly distributed PV systems.

VI. Conclusions

The developed solar variability analysis tool can quantify daily variability and ramp rates for different PV system layouts. System operators can use this tool to predict hourly schedules for transferring between balancing areas, but operators still need to maintain balance between generation and load.

While analysis of hourly variation can be of some use in scheduling and dispatch of power, it is not sufficient to understand real-time operation and control impacts and to properly plan for and accommodate them at both the bulk power system and distribution system levels. At the distribution level, feeder and utilization voltages must be maintained with limits, and, system protection and restoration schemes must continue to function properly, and, PV cannot be allowed to impair reliability. At the bulk power system level, the NERC Resource Subcommittee (RS) defines the control performance requirements for the assessment of control area generation control performance in the Control Performance Standard 1 (CPS1), Control Performance Standard 2 (CPS2) and Disturbance Control Standard (DCS) standards. In order to comply with these standards, system operators need to maintain frequency and area control error even in the presence of intermittent generation. NERC standards are likely to be updated as recommendations emerge from efforts such as the Intermittent and Variable Generation Task Force (IVGTF). There is a need to collect 1-min (or shorter) solar irradiance or PV production data from multiple sites in regions with potential for high PV penetrations and develop models to understand aggregate variability and impact on system operation, and the potential for PV to even perform useful ancillary services such as voltage or frequency support in a future grid with much greater PV penetration levels.

VII. Future Work

Future work will involve the investigation high temporal resolution data, with particular interest in the clearness index, which as described above, can eliminate much of the seasonal and location specific effects and better quantify the predictability of various deployment scenarios due to short term weather changes (e.g. clouds).

Enhanced resolution data would be required to better determine irradiance and climatic differences along the coast of Florida. Higher temporal resolution data will also require a modified tool for power simulations, as SAM is presently limited to hourly weather data.

VIII. Acknowledgment

The authors gratefully acknowledge the team at Clean Power Research, LLC, who provided the authors access to 11 years of Florida-wide meteorological data. We also thank Paul Gilman of the National Renewable Energy Laboratory for his assistance with aspects of the SAM software, James Haggard of FSEC for assistance with scripting, and William Wilson of FSEC for his initiative and ongoing work with the 3kW PV system high-speed data collection described in this paper.

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X. Biographies

David K. Click (M ’11) received a BSEE degree in 2001 and MSEE degree in 2004, both from the University of Virginia. Dave has been a senior research engineer at the Florida Solar Energy Center for over four years, with interests in high-penetration levels of distributed generation and photovoltaic codes and standards.

Houtan Moaveni received a BSEE degree in 2007 and MS degree in Energy Systems and Management in 2008. He has been a research engineer at the Florida Solar Energy Center for three years, with interest in high-penetration levels of distributed generation and utility-scale solar power plants.

Kristopher O. Davis (M ’07) received a BSEE degree in 2007 from the University of Central Florida (UCF) and a M.S. in Optics in 2011 from the College of Optics and Photonics at UCF. Kris has been a research engineer at the Florida Solar Energy Center for over three years, and his current research interests include photovoltaic cell fabrication methods, solid-state device physics, module reliability, and systems integration.

Richard H. Meeker, Jr. (M ’04, SM ’06) is responsible for industry partnerships and U.S. Dept. of Energy-funded electric power reliability projects at FSU’s Center for Advanced Power Systems (CAPS). He is also involved in research, development, and education activities in control systems, electric power, energy systems, and modeling and simulation for applications in electric utility, industrial, commercial, and shipboard application. Rick is a licensed P.E. in Florida and Georgia, is a senior member of IEEE and ISA, is active in leadership of ASME Tallahassee Section and a member of the ASME National Energy Committee, and is a member of ASNE, SNA, and several regional and local energy advisory groups.

Robert M. Reedy (M ’70) received a Bachelor of Engineering and M.S. from Auburn in 1973 and 1975, respectively, and a M.B.A. from Florida Southern College in 1990. Bob has been Director of the Solar Energy Division at FSEC since early 2007. Previously, he was four years with the Georgia Transmission Corp. as Research Manager and as Manager of Transmission Line Design. Other experience includes VP/COO of Turbec North America (microturbines), Marketing Manager with The Energy Authority, Inc. (wholesale energy marketing), and 13 years with Lakeland Electric Utilities as Director of their Engineering and Operations group (including system control and interconnected operations).

Anthony Pappalardo is a senior engineer at the Florida Solar Energy Center. Tony has studied physics and computer science at the Florida Institute of Technology, and he has previously done work in modeling and simulation involving thermodynamics and optics, as well as in developing high speed cluster computing systems.

Rodica Krueger (M ’11) received a BSEE degree with a minor in Power Systems Engineering in 2007 from the Polytechnic University of Timisoara, Romania and is currently pursuing a MS in Industrial Engineering and a MS in Electrical Engineering at University of Central Florida. Rodica has been a Graduate Assistant at Florida Solar Energy Center for a year, and her current interests are long-term performance and degradation rates of photovoltaic systems, as well as small-scale distribution and interconnection of clean energy systems.