Day Ahead Irradiance Forecast Variability Characterization Using Satellite Data

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***Abstract* — In this paper we address the use of satellite- based irradiance data as a proxy for the ground irradiance data to determine the intraday solar variability as a function of a finite difference of hourly clear sky index, here after called nominal variability. The satellite data based nominal variability is compared to that of the ground data based variability to determine the use of satellite data as replacement for ground data for this application. A mathematical relationship has been developed to predict nominal variability as a function of the day's clear sky index. The article also demonstrates the application of the intraday variability to predict day ahead hourly forecast variability range as a function of the day's clear sky index.**

The results show that the intraday solar irradiance variability can be calculated using historical satellite data and provides a similar result to that of variability computed using quality historical ground data. The results also show the potential of intraday solar variability to characterize day ahead forecast variability.

***Index Terms* — Satellite data, solar forecast, solar resource, intraday variability, forecast variability, solar resource modeling.**

I. Introduction

The inherent variability of wind and solar radiation affects the price that variable renewable energy generators receive on the market. For example, during sunny times the additional electricity supply from photovoltaic (PV) sources can reduce demand driving down energy prices. Because the drop is larger with more installed capacity, the market value of solar power falls with higher penetration rate.

According to the recent study conducted by MERCOM CAPITAL GROUP ([1]), the installed capacity for solar power is projected to increase globally (Figure 1). This growth in the solar power is in response to interest in low-emissions power sources and a desire to decrease the global dependence on petroleum and in response to climate change. According to a report by US Energy Information Administration (EIA) ([2]) most projections of U.S. electricity growth from wind and solar generations are due to a strong push from state and federal policy through subsidies and renewable portfolio standards. For example, EIA expects renewable sources to constitute 25% of the increase in total generating capacity across the electric power sector between 2013 and 2018.

Due to the variability of solar power sources and increasing penetration of solar generation on energy grids, independent system operators and balancing authorities are facing a high level of uncertainty in an expected solar resource for managing the grid. System operators use day-ahead load forecasts to help schedule the amount of energy needed for each hour of the next day.

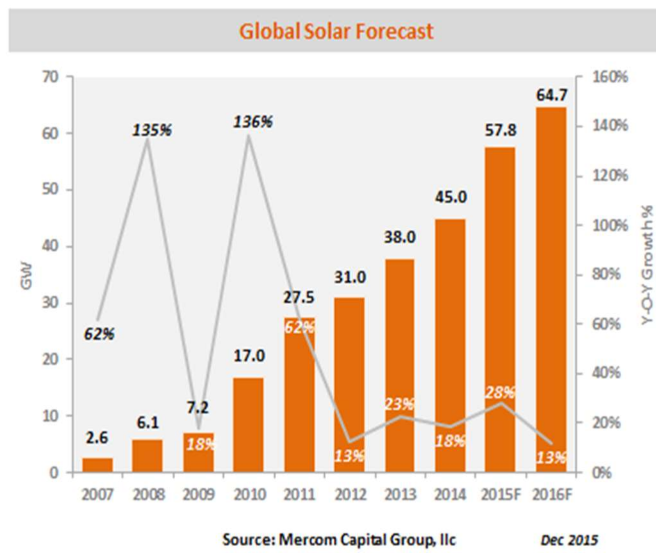

Fig. 1. Global solar power growth forecast from Mercom Capital Group.

Forecasts of solar energy can be used to address expected variability and uncertainty in the solar resources and it is playing a key role in solar PV operation and management, accurate solar power dispatchability as well as scheduling. Therefore, providing the system operators with an accurate day ahead solar energy forecast and information on the forecast variability will help them make early decisions about how much electricity will be needed from other, non-solar sources. However, the variability and uncertainty in solar power forecast and solar resource assessment is different from the traditional, dispatchable generation resources and it is difficult to be easily integrated into standard system operating procedures.

Solar irradiance variability can be determined by both deterministic and stochastic signals. The deterministic signals have both seasonal and diurnal variation and can be determined using simple astronomical relationships. However, atmospheric conditions, such as water vapor, turbidity, and clouds are the most influential on the solar energy reaching the ground and they are variable in nature. Clouds are the most significant variable of the three, yet are the most difficult to predict with the highest certainty.

The forecasting of solar energy production faces issues similar to those for wind. However, solar forecasting has significant predictability because the sun's path through the sky is known. Nonetheless, solar resource forecasting is not as mature as the wind forecasting. However, Clean Power Research's SolarAnywhere V4 is a whole lot more reliable than wind forecasting.

The overall shape of solar energy production can be easily predicted for most of the time if the weather is clear from cloud cover, but significant errors in the level and timing of solar energy production are introduced by the passing of clouds that cause ramps (sudden increases or decreases) in energy production.

There are several state of the art solar power forecasting models as a function of the applications, time scales and spatial resolution needs. Very short-term forecasting in a temporal range of 30 minutes to 6 hours is based on the analysis of satellite data. Forecasts for 6 hours to 7 days ahead are based on Numerical Weather Prediction (NWP). Figure 2 illustrates the different forecasting techniques as a function of time and spatial scales.

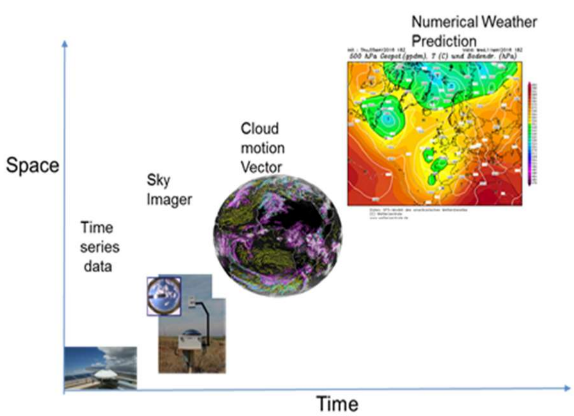

Fig. 2. Various techniques of solar forecasting ranging from site production data (seconds-to-5 minutes ahead), sky imagers (5 min to 30 min ahead), satellite-based cloud motion vector (30 min – 5 hours ahead) to numerical weather prediction (5 hours – 7 days ahead).

NWP and statistical models are used to predict day ahead and longer period energy outputs from variable generation driven by solar and wind energy. Successful integration of solar power into electricity grids begins with a reliable day-ahead NWP forecast. NWP models depend on what is happening now (initial condition) to predict the future (equation 1 shows example of simplified NWP equations)

$$\theta^{n+1} = \theta^{n} + \frac{\partial \theta}{\partial t} \Delta t \qquad (1)$$

However, it is hard to accurately measure current atmospheric conditions due to sparse measurements and instrument errors, unresolvable/sub grid-scale processes that must be parameterized, gaps in the observations, and the need for interpolation. Models are also constructed with imperfect physics and parameterization that makes it difficult to resolve small scale processes. The cumulative effect of model uncertainty, incomplete and in accurate initial conditions, and coarse spatial scales are some of the reasons why NWP models have difficulty to accurately predict small scale clouds, especially over a single site.

However, solar energy forecasting variability can be reduced by aggregating forecast over geographical regions to help improve the accuracy of NWP forecasts [7]. In this paper we demonstrate a method by which intraday variability can be imparted into a NWP-based solar energy forecast for a particular site on a day ahead basis.

The basis for this paper is the concept introduced by Lauret et al. 2015 [3] in which the authors characterized intraday irradiance variability (or "nominal variability") as a function of the standard deviation of the finite difference of clear sky index (ratio of observed global horizontal irradiance (GHI) to clear sky irradiance GHI_clear) between consecutive time steps. Lauret et al. 2015 have investigated the relationship between nominal variability and daily clear sky index and have derived an elegant polynomial relationship. For their investigation of intraday irradiance variability, the authors used Irradiance data from SURFRAD stations. SURFRAD stands for Surface Radiation Network operated and maintained by National Oceanic and Atmospheric Administration (NOAA). Another NOAA stations that provide historical good quality data are the Integrated Surface Irradiance (ISIS) stations network. Over all there are 16 NOAA stations and the minimum distance between a pair of the stations is ~200 km. Research shows that the correlation between ground stations falls quickly with distance and satellite derived irradiance values have been shown to be more accurate compared to ground measurements beyond 25 km from a ground station [5]. This shows that using ground stations data for study such as irradiance variability caused by small scale systems makes the study very localized and lacks applicability beyond the study area. The authors of this paper are extending the work of Lauret et al. 2015 by using the satellite data at the locations where the SURFRAD data has been used to replicate the results. Such work will make it easy to study intraday irradiance variability at locations where there is no long term ground data. The advantage of the satellite based data is that it is available everywhere within the satellite field of view coverage.

Because of the fact that forecasts are not perfect, excess dispatchable generation capacity must be procured to ensure reliability in the operation of the grid. For grid balancing and other tasks related to variable energy sources, an understanding of the variability associated with the forecast is important for planning of unit commitment and scheduling purposes. In this study we are also attempting to use the site intraday variability to enhance our estimates of day ahead forecast variability.

The remainder of the paper is organized as follows: In Section II we start with a description of the data and methodologies used in the nominal variability calculation. We then show results from the intraday variability of irradiance using the SURFRAD measured and SolarAnywhere® historical satellite-based irradiance data. In section III we also evaluate day ahead forecast upper and lower variability bounds as calculated using the polynomial relationship built from the daily clear sky index (KT*). In section IV we discuss results and present summaries.

II. Data and Methodology

Four SURFRAD stations were chosen for this study: Desert Rock, NV, Fort Peck, MT, Goodwin Creek, MS, and Penn State, PA. Irradiance data have been obtained for these stations from 1998 to 2015. Corresponding SolarAnywhere GHI and clear sky GHI data spanning the same timeframe was obtained for the SURFRAD station locations. The forecast models used in this study are derived from the European Center for Medium Range Weather Forecast (ECMWF), NOAA's Global Forecast System (GFS) and National Digital Forecast Database (NDFD).

Lauret et al. 2015 [1] has shown that the nominal variability can be determined from the day's clear sky index. We used a similar methodology for calculations of nominal variability and then fitted a polynomial model to establish a relationship between the nominal variability and the daily clear sky index.

The following equations show how the clear sky index is computed on an hourly basis (equation 2) and on a daily basis (equation 3). The nominal variability is calculated as the absolute values of finite differences of hourly clear sky index values (equation 4).

$$kt_j^* = \frac{GHI_j}{GHI\_clear_j} \qquad (2)$$

$$KT^* = \frac{\sum_{i=1}^{n} GHI_i}{\sum_{i=1}^{n} GHI\_clear_i} \qquad (3)$$

$$\sigma(\Delta Kt) = \sqrt{var(\Delta Kt)} \qquad (4)$$

Where $\sigma(\Delta Kt)$ *is called a Nominal Variability*, GHI_i is Global Horizontal Irradiance data at time j. GHI_clear_i is SolarAnywhere data without clouds (Clear Sky Global Horizontal Irradiance) at time j. KT* is an average clear sky index of a day (daily clear sky index) and kt* is hourly clear sky index from which nominal variability is calculated. Further details on the use of kt* for site specific irradiance parametrization can be found in Perez et. al 2011 [4]. Ideally, the values of kt* varies from 0, when the weather is overcast to 1, when it is clear sky. Under variable cloudy conditions the values of Kt is above zero and below one.

In this paper we investigate the use of SolarAnywhere irradiance data in-lieu of ground measurement data to calculate the nominal variability (substituting SolarAnywhere data instead of ground data in the equations 2 and 3) to augment the use of ground data for applications where there is no ground data available to work with. We have also calculated the nominal variability as a function of season. For this study we used only two seasons, which we call cold and warm season. cold seasons are defined as months from October to March while warm season is defined as months from April to September. We then fitted a polynomial model for KT* versus $\sigma(\Delta Kt)$ and used the model parameters to calculate the nominal variability of day-ahead NWP hourly forecasts.

III. Results Preview

A. Comparison of nominal variability as calculated using ground and SolarAnywhere data

The nominal variability (equation 4) has been calculated using both SURFRAD and SolarAnywhere data. We classified the data in to two categories called cold and warm seasons. The polynomial model is fitted to the data and shown in the figures 3, 4, and 5. Figure 4 and 5 are for warmer months of Penn State in Pennsylvania and Fort Peck in Montana for eastern and western United States. The x-axis is daily Kt value calculated as the mean of an hourly Kt based on the equation 3 and y-axis is the nominal variability calculated as per equation 4. The figures show that the results are independent of climatic regimes since both daily Kt and Nominal variability are unit less and purely a function of the ratio of GHI to clear sky irradiance values. From the figures it can also be seen that in the middle of the daily Kt values the nominal variability values are more scattered and the values converge to zero as the daily Kt value goes to 1 or zero, for an overcast and clear sky conditions respectively. That means that when the irradiance profile has a uniform shape (like that of clear sky day) the Nominal variability converges to zero due to symmetry of the profile (the nature of finite differences), and the same holds true for completely overcast days. From the figures we can also see that the polynomial fit has more curvature during the warmer season (Figures 4 and 5) compared to the colder season (Figure 3). The reason why the warmer seasons have much more variability compared to the colder seasons is likely due to the occurrence of cumuliform and convective clouds during the warmer seasons.

The distribution of the data and the nature of the polynomial model has a very similar parameter values between the SolarAnywhere data (left panels in the figures) and that of SURFRAD stations data (right panel in the figures). This experiment has been conducted for all of the SUFRAD stations (not shown) and the patterns in the observations are the same across all stations and seasons. Therefore, the SolarAnywhere data can be used as a proxy for ground data to calculate intraday solar resource variability.

B. Day-ahead irradiance forecast characterization

We then investigated day-ahead NWP forecast model variability performance for the days with clear sky index values ranging from 0 to 1, focusing on days with nominal variability between 0.4 to 0.7. Figure 6 shows the bias of the day-ahead irradiance forecast values from ECMWF NWP model output. In this case the bias is defined as the difference between forecast and ground measurement. The forecast bias is very high when the KT* values are between 0.4 and 0.8 and skewed to the left. The skewness showed that the forecast under predicts when there are small scale clouds (not overcast or not clear sky, but scattered cloudy conditions. Some places show very tight distribution and those are places dominated by sunny conditions (example Desert Rock in Nevada). Figures 7 and 9 show a scatter plot of SURFRAD ground data versus ECMWF day ahead irradiance forecast values. The bias of the forecast is investigated for two cases. a) The case when the daily clear sky index values are between 0.4 and 0.7, resulting in a higher scatter in Nominal variability and b) For the days with daily clear sky index values over 0.7, where the Nominal variability converges to values close to zero.

The scatter plot in Figure 7 shows that the relationship between ground measurement data at four SUFRAD stations and the ECMWF day ahead forecast values diverge away from one to one line and there are more scattered points as the irradiance values increase. The divergence at higher irradiance values could be due to convective systems developing when the atmosphere gets hotter. Figure 8 shows the bias (ECMWF-SURFRAD) as a function of the time of the day. The figure shows that the forecast performance for daily Kt (KT^*) values between 0.4 and 0.7 gets worse at high sun hours. This shows that during these hours the clouds develop and cause the higher variability that has been shown in the nominal variability plots (Figures 3, 4 and 5).

Therefore, there is a need to characterize forecast performances during such hours when the forecast has trouble capturing small scale systems and performs bad. However, the days with clear sky index over 0.7 do not have a wider scattered points as those days with clear sky index between 0.4 and 0.7 (Figure 9). In this paper we have attempted to use information from the intraday irradiance variability characterization (nominal variability) to understand the possible variability in the day ahead forecast. Figure 10 shows an example of a day ahead forecast variability as a function of the weather condition.

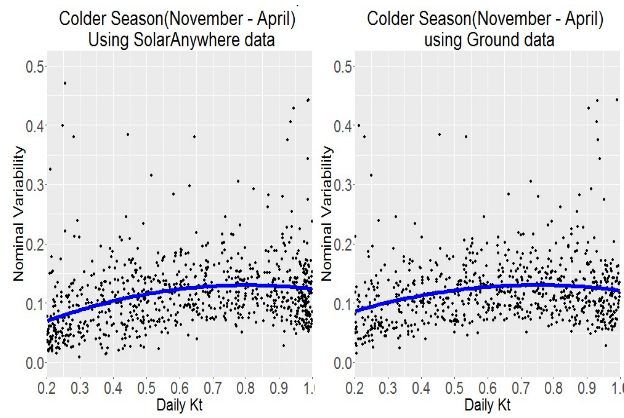

Fig. 3. Nominal variability as a function of Daily Kt for the cold season at Penn State, PA SURFRAD station.

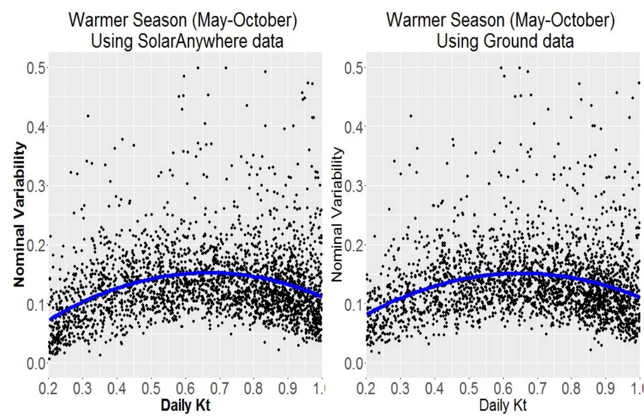

Fig. 4. Nominal variability as a function of Daily Kt for the warm season at Penn State, PA SURFRAD station.

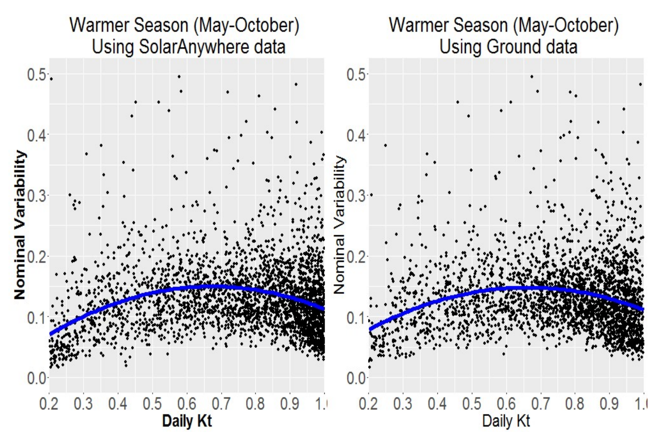

Fig. 5. Nominal variability as a function of Daily Kt for the warm season at Fort Peck, MT SURFRAD station.

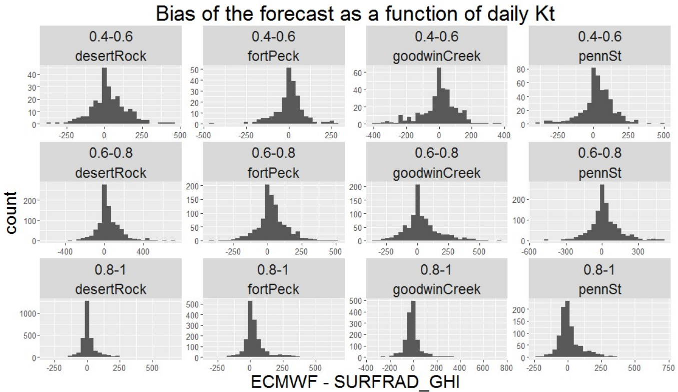

Fig. 6. ECMWF day-ahead forecast bias as a function of daily Kt at four SURFRAD sites.

In Figure 10 the orange line is clear sky irradiance value, blue line is ground data and the gray shaded region shows an envelope of maximum and minimum day ahead forecast values as calculated from the nominal variability model. The figure shows very low day ahead forecast variability in the clear days and higher variability in the case of scattered cloudy days.

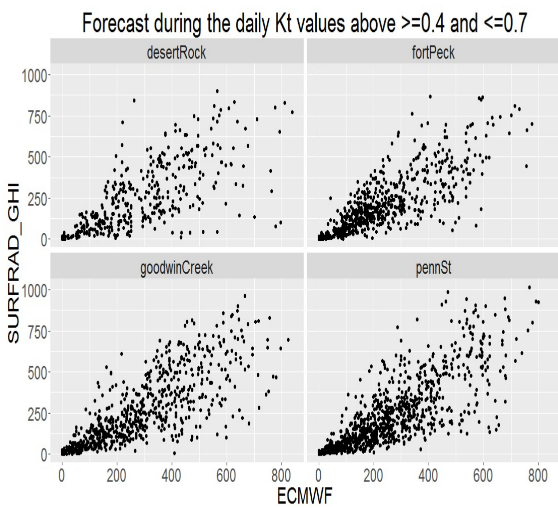

Fig. 7. ECMWF day-ahead forecast vs SURFRAD site ground data at four SURFRAD sites for KT* between 0.4 and 0.7.

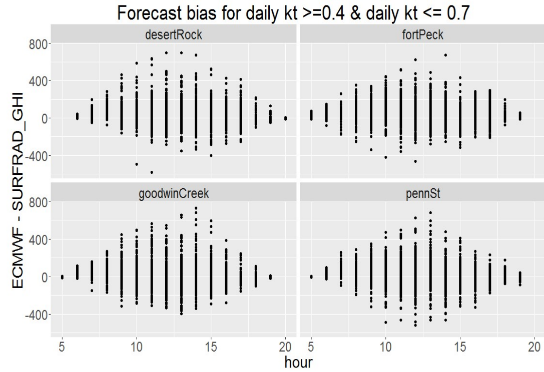

Fig. 8. ECMWF day-ahead forecast performance as a function of time of day at four SURFRAD sites.

Since the polynomial model fitted to the nominal variability is derived from 18 years historical SolarAnywhere data we can have confidence that the model captures the full range of possible weather conditions at a site. We cap the maximum forecast variability value by the clear sky value to properly constrain our envelope of predicted variability. Figure 11 illustrates a day-ahead forecast where the maximum forecast variability is constrained by the clear sky upper bound. This is an example where, unlike wind, having a clear sky value will help to make sure that the model output will not exceed a physical value.

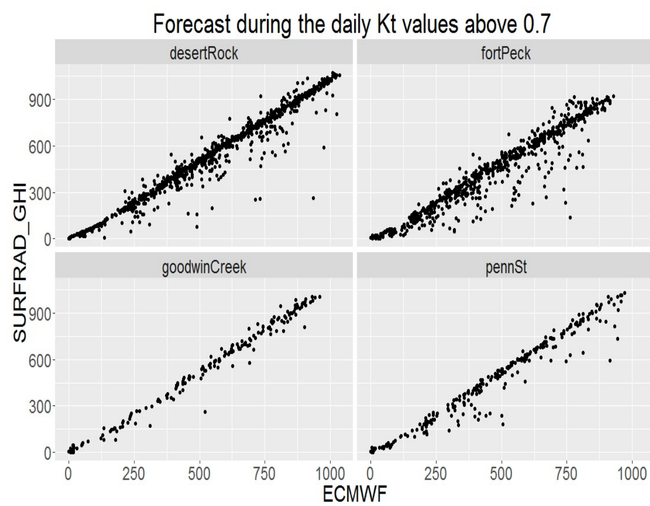

Fig. 9. ECMWF day-ahead forecast vs SURFRAD site ground data at four SURFRAD sites for KT* greater than 0.7.

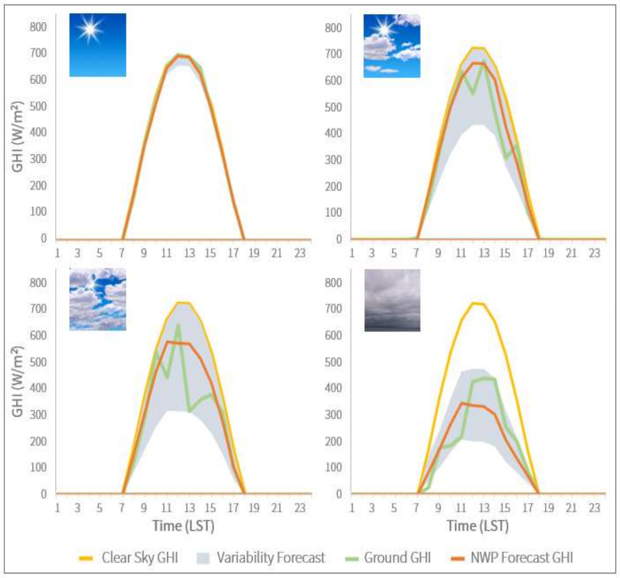

Fig. 10. Example of forecast variability characterization using nominal variability under various clear-to-cloudy sky conditions.

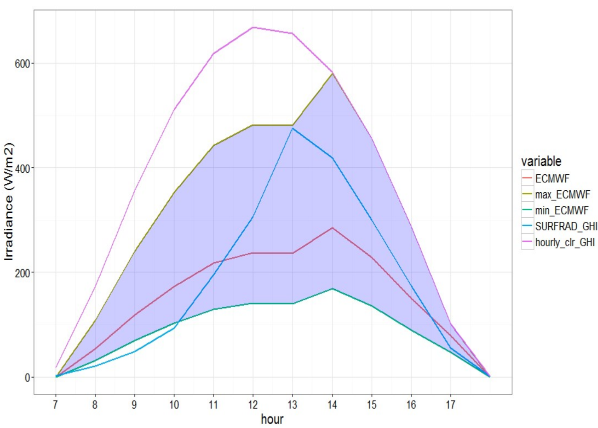

Fig. 111. Example of forecast variability values that are capped at the clear sky upper bound.

IV. Summary

The use of satellite-based irradiance data as a valid proxy for the ground data to determine historical site-specific intraday irradiance variability has been demonstrated in this paper. Having 18+ years of historical satellite data will help to capture variety of weather events that can influence the solar irradiance at a site and enable one to model site-specific irradiance variability. The nominal variability models demonstrated here can help characterize the day-ahead NWP forecast variability. The difference in the shape of the polynomials fitted to the nominal variability as a function of warmer and colder seasons suggests the need to further investigate the nature of the nominal variability model on monthly or sub-monthly basis.

The forecast variability characterization results shown here are applicable to improving the hourly variability associated with a day-ahead NWP-based irradiance forecasts. Additional work will be performed validating the ground-to-satellite data intraday variability connection and day-ahead forecast impacts at additional locations around the USA.

We have also noticed the forecast performance differences between the different NWP models as a function of clear sky index which suggests the possibility of this approach to help improve the models by correcting the biases with the help of the nominal variability index. The research suggests the need for more work to make the model more useful and to explore areas that have not been considered in this work.

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