DISSERTATION PROPOSAL: DESIGN AND USE OF AN IRRADIANCE MONITORING NETWORK FOR SHORT-TERM IRRADIANCE FORECASTING

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Abstract

Short-term irradiance forecasting is of great use to electric utilities to understand the solar resource for solar power plants and maintain a reliable grid. This dissertation studies new methods to produce short-term forecasts that rely on an irradiance monitoring network. As part of this forecasting effort, we designed and deployed inexpensive irradiance sensors in Tucson, AZ. These sensors, along with data from rooftop PV systems, are used to produce irradiance forecasts for 1 min to 60 min in the future. For longer time horizons (30 min to 4 h), forecasts produced from satellite images are used. We have improved the irradiance estimates of individual satellite images by combining the satellite estimate and data from the sensor network. These improved satellite derived nowcasts will be the basis of future work that will continuously assimilate data into satellite derived forecasts.

1 Introduction

Solar power forecasts help control the costs associated with the intermittency of solar power [1] by, for example, enabling smarter control of battery storage to control ramp-rates and provide frequency support [2, 3] or more efficiently scheduling generators. Since global horizontal irradiance (GHI) is the primary driver of non-concentrating solar power production, forecasting techniques often first forecast GHI and then produce a power forecast [4, 5]. For forecast horizons from a few seconds to a few minutes, statistical techniques applied to data from ground sensors are often used [6, 7]. Intra-hour forecasts may use a sensor network [8], machine learning techniques [9], or sky cameras [10]. Forecasts based on satellite images are used for time horizons from roughly 1 h to 6 h in advance [11], while numerical weather predictions are used for forecasts horizons extending from many hours to many days in advance [12].

The goal of this dissertation is to study, in depth, short-term forecasting techniques that rely on data from a sensor network. First, we describe the sensor network that we built in Tucson, AZ for this purpose. Then, we describe forecasts for 1 min to 1 h in advance using only data from this network [13]. We studied forecast errors in depth as part of this work to understand that simple error metrics may not be enough to determine which forecasting method is "best." For longer time horizon forecasts, which require estimates of irradiance over a larger area, satellite images are ideal starting points. One problem is that the initial satellite estimate, or nowcast, often has large errors when compared to ground measurements. Utilizing the network data and a method known as optimal interpolation (OI) we improved these satellite nowcasts to more closely resemble reality [14]. Future work (by other students) will focus on extending OI with a cloud advection scheme to continuously assimilate new ground and satellite data, and to combine the forecasts that are made for different time horizons into a single, unified forecast. A summary of the errors for methods studied in this dissertation is presented in Fig. 1.

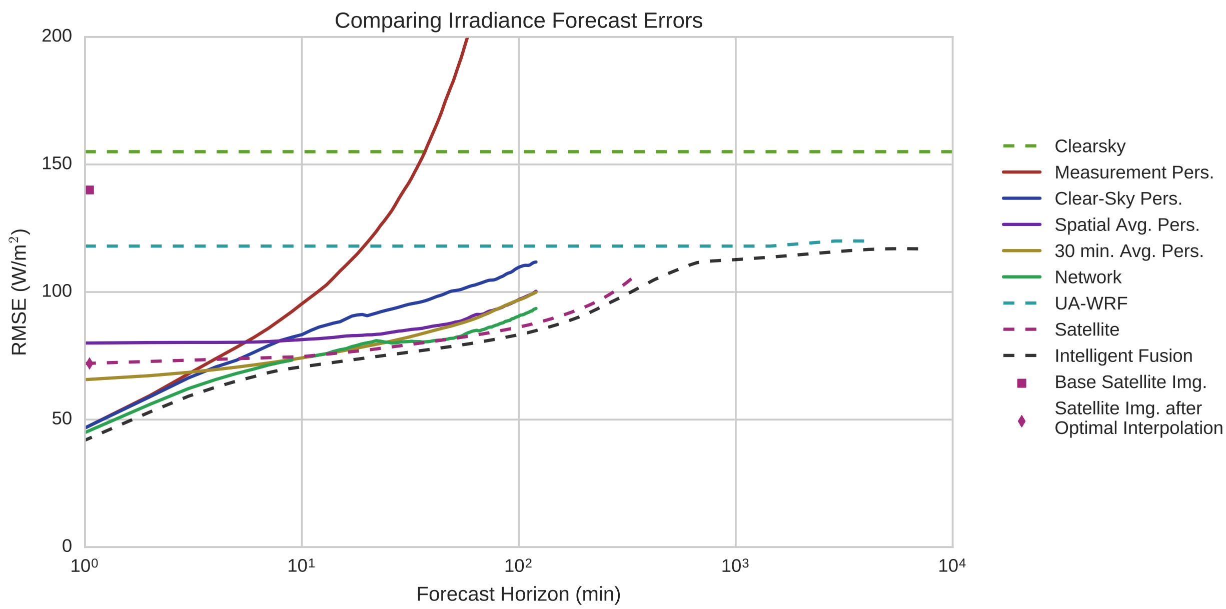

Figure 1: A comparison of irradiance forecast root-mean squared errors (RMSE) across many time horizons. The solid lines (and points) indicate forecasts that will be studied in depth in this dissertation. Dashed lines are based on prelimnary analysis, but have not been studied in depth. Pers. refers to persistence, and UA-WRF refers to the numerical weather models generated at the UA using the Weather Research and Forecasting (WRF) model. The intelligent fusion is a theoretical combination of forecasts at diffferent time horizons for the best forecast at all horizons.

2 Irradiance Monitoring Network

Lonij *et al.* described forecasts made using an network of rooftop PV systems as sensors [8]. To extend and to provide this type of forecast to utilities operationally, we built an irradiance montioring network with the primary goal of receiving data in real-time and with sufficient density to produce accurate forecasts. This led to the construction of the irradiance monitoring network.

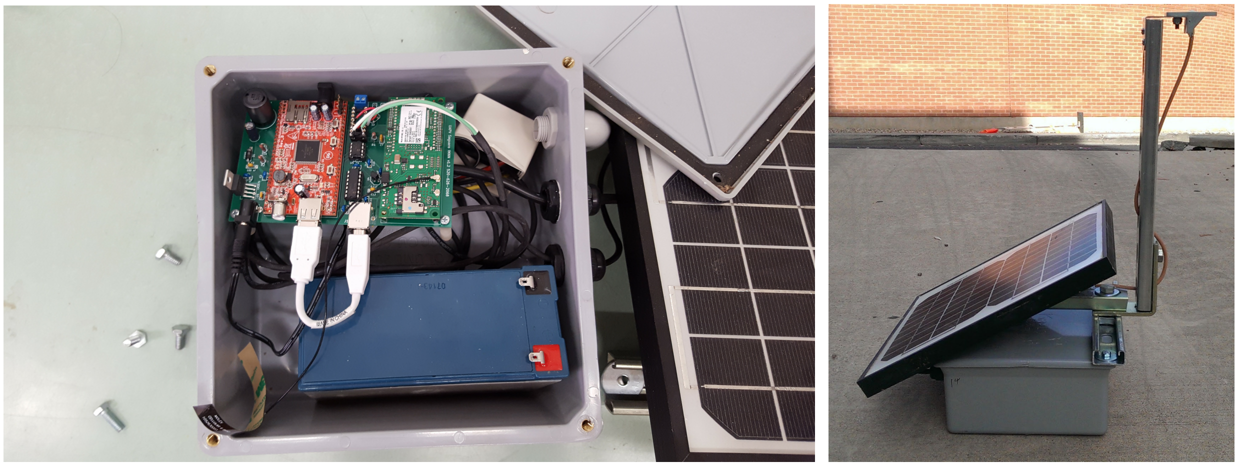

Figure 2: Photos of the interior and exterior of the custom sensors used in the irradiance network.

We iterated through a number of designs before arriving at the design shown in Fig. 2. The sensors utilize a small Linux computer to collect the data from a photodiode sensor, a solar panel and battery for power, and a cell modem to send the data to a central server every minute. These sensors provided high quality data from April to July 2014 before a flaw with the installation method killed many of the sensors.

With the help of Technicians for Sustainability, we also receive data from rooftop PV systems every five minutes. A map of the sensor network is shown in Fig. 3.

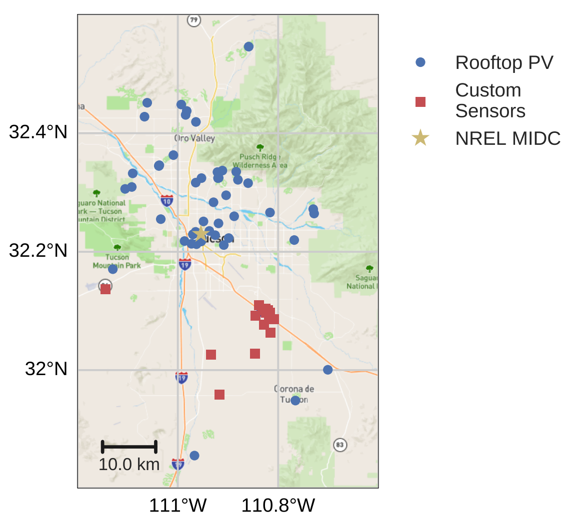

Figure 3: Map of Tucson, AZ, indicating the locations of custom and rooftop PV sensors. The NREL MIDC star refers to the calibrated and maintained irradiance sensor located at the University of Arizona.

3 Irradiance Network Forecasts

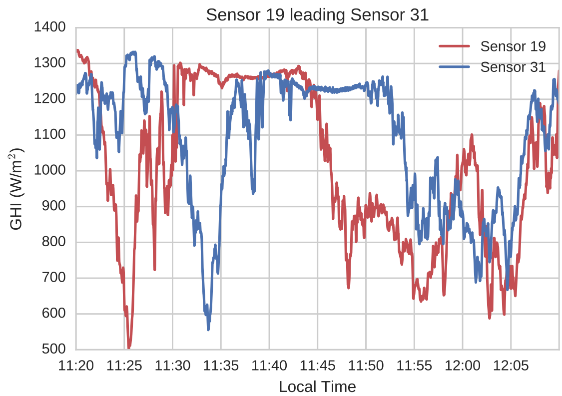

Figure 4: An example of the output of sensor 19 (red) predicting what the output of the upstream sensor 31 (blue) in roughly 8 minutes.

The basic idea behind the irradiance network forecasts is that a drop in the GHI recorded by one sensor may predict a future drop in GHI at another sensor downstream as illustrated in Fig. 4. To make the forecasts based on the irradiance monitoring network, we first interpolate data from the sensors to produce a kind of cloud map. This map could then be translated based on some derived cloud-motion vector to generate a forecast.

We have shown that a forecast made in this way outperforms a persistence model that incorporates the diurnal cycle of GHI. We also found that spatial or time averaging can produce skillful forecasts which led to an in depth study of how one might present error metrics in a Taylor diagram to determine the best forecast. Errors for these forecasts are shown in Fig. 1.

4 Optimal Interpolation of Network Data and Satellite Images

Optimal interpolation (OI) is a Bayesian technique to combine the two pieces of information accounting for the relative error between them. We were able to apply OI to correct satellite estimated GHI with data from the ground network even at locations in the image without nearby sensors. An example of the improvement due to OI is shown in Fig. 5 and the improvement in RMSE over 3 months is shown in Fig. 1.

These nowcasts of GHI using a satellite image provide broad areal coverage which is useful for estimating the generation of distributed, rooftop PV systems and for resource assessment. When combined with a cloud advection model, OI can be extended to the well known Kalman filter and one can continuously incorporate new data into the forecast.

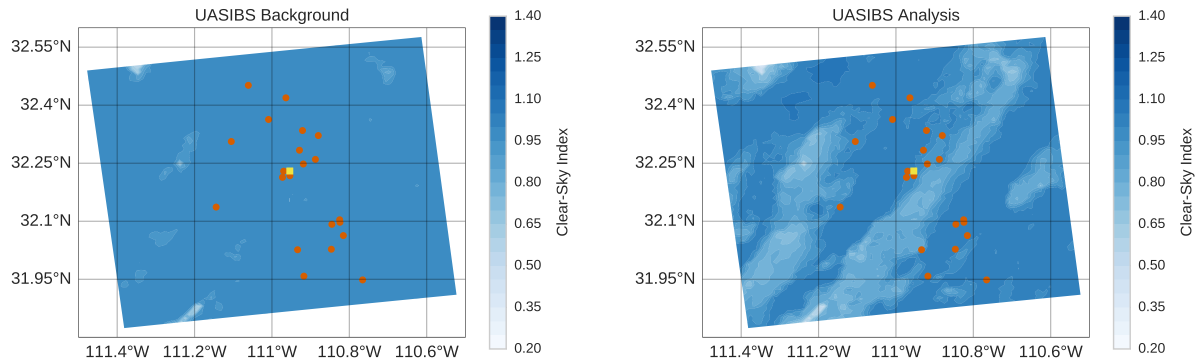

Figure 5: An example of the satellite estimate clear-sky index (GHI / GHI_{clear}) before (left) and after (right) OI. The initial satellite estimate failed to produce enough clouds but OI corrects this.

5 Conclusion

This dissertation explores the use of an irradiance monitoring network to improve solar irradiance forecasts that help electric utilities use more solar power. First, an irradiance monitoring network was designed and deployed [15]. Then, data from this network was used directly to produce irradiance forecasts that show an average of 20% skill over a high-quality persistence method [13]. Finally, the data from the network was used to correct satellite derived irradiance images that will be the basis of forecasts in the future [14]. Future work in the group will continue to solidify the dashed lines in Fig. 1 to produce the best irradiance forecasts at all time horizons.

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