Solar Energy Forecast Validation for Extended Areas & Economic Impact of Forecast Accuracy

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***Abstract* — This article evaluates the accuracy of solar forecast model as a function of geographic footprint ranging from a single point to regions spanning several hundred km. The forecast models include SolarAnywhere, ECMWF, GFS, HRRR, NDFD and satellite-based cloud motion. The forecast time horizons range from one hour ahead to 2 days ahead. In addition a new accuracy metric is introduced: this metric quantifies the cost of remedying forecast errors with backup generation if the forecasts overpredict, or with curtailment in case of underprediction.**

***Index Terms* — solar forecast, solar resource, backup, curtailment, modeling.**

I. Introduction

Operational solar forecasts are increasingly applied regionally to support grid operators to account for the impact of dispersed PV generation on their load forecasts [e.g., 1]. However, while regional aggregate forecast error reduction has been noted (e.g., [2]), in depth quantitative validations have typically been site-specific (e.g., [3, 4]). In this article we systematically analyze the influence of the solar generation footprint on the accuracy of operational solar forecast models.

Starting from a single point and gradually extending the area to a subcontinental region, we analyze the evolution of forecast accuracy. In addition to standard model evaluation metrics we also pay attention to the logistical accuracy of PV output forecasts by estimating the cost of missed forecasts from the underlying drivers of energy markets: specifically, we estimate the amount and cost of backup energy and capacity as well as solar output curtailment needed to make-up for forecast errors, hence to provide the equivalent of firm, guaranteed forecasts with 100% reliability.

II. Methodology

We consider two climatically distinct US regions centered respectively on the SURFRAD measurement stations of Desert Rock, NV, and Bondville, IL. Around each station we also analyze concentric regional footprints ranging from one single intermediate resolution satellite model cell (~ 10 x 8 km) to 110x110 such cells (amounting to a region the size of Texas and Oklahoma.) For extended areas, the forecasts are evaluated against SolarAnywhere historical data. This extended area evaluation benchmark is justified by: (1) the fact that single point forecast errors gauged against ground measurements and satellite data are comparable (see Figure 1); (2) the satisfactory performance of new satellite models compared to ground [5], and (3) the observation that satellite model errors diminish considerably when gauged against an aggregate of points.

The forecast models that are analyzed in this article include the recently deployed SolarAnywhere (SA-V4) [4] as well as its constituting underlying forecast models, including NOAA's Global Forecasting System (GFS), High Resolution Rapid Refresh (HRRR) and National Digital Forecast Database (NDFD), The European Center for Medium Range Weather Forecasts (ECMWF), and satellite-derived cloud motion vectors (CMV) forecasts. The time horizons considered for this analysis include 1, 3, 24 and 48 hours-ahead.

Experimental data: the results for the final paper will be based on forecasts and benchmarking data spanning nearly one year from June 2015 to April 2016. Both global irradiance (GHI) and simulated nominal PV output (at 30-degree tilt and south facing) will be evaluated.

Validation Metrics: These include the standard model validation metrics: mean bias, mean absolute, and root mean square errors (respectively MBE, MAE and RMSE). In addition a new metric is introduced to quantify the cost of missed forecasts on the basis of first operational principles: this metric quantifies the amount of backup capacity and backup energy necessary to make up for any forecast overestimation through the period analyzed. The cost of missed forecast can then be estimated from the cost of backup technology, e.g., electrical storage via batteries. This operational metric also quantifies the amount of solar that must be curtailed in case of forecast underestimation. In essence the metric estimates the cost of providing 100% accurate solar forecasts from the added hardware and operational losses associated with solar production.

III. Results Preview

This preview is based on a preliminary subset of the data spanning 10/15 to 12/10/2015, and focuses on GHI.

Figure 1 compares the relative RMSE statistics obtained when using ground measurements and satellite irradiances as a benchmark. The similarity of these statistics warrants the use of satellite-data for regional validations.

Table I reports the relative MAE (MAPE) of all forecast models at one-hour ahead as a function of footprint. Table II shows the same but for 24 hours ahead. For both eastern and western locations, the impact of footprint on model performance is noteworthy. At one hour ahead, MAPEs of less than 5% are observed for regional footprints of ~ 100x100 km. For day-ahead, MAPEs of the order of 10% are observed for a regional footprint of ~ 40x40 km in the west. In the eastern US, day-ahead MAPEs of 15% are achieved for footprints greater than 200X200 km. In all instances the SolarAnywhere V4 performance is superior to that of its underlying models.

The scatterplots in Figure 2 qualitatively illustrate the influence of footprint on the day-ahead performance of SA-V4 for Desert Rock. The plots correspond respectively to a single location, and to 2^o x 2^o, 4^o x 4^0, and 7^o x 7^o, extended areas, i.e. corresponding to regional areas roughly equivalent to of Massachusetts, New York, and California. These scatterplots show that the reliability of day-ahead forecasts becomes remarkable as the considered balancing area increases.

The new operational metric is illustrated in Table III. The table reports the % of solar energy that must be curtailed and, vice versa, supplied via backup generation to make up for any forecast deficit or overestimation, i.e., to render the forecasts 100% accurate. The tables also report the cost of battery storage that would be sufficient to absorb excess production and provide backup generation if storage was applied to absorb excess and provide backup generation – using $300/kWh for battery CAPEX and 80% roundtrip efficiency.

References

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TABLE I
Hour-Ahead MAPE Statistics

BONDVILLE						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMV
0.1 x 0.1	10.3%	16.1%	26.4%	21.5%	31.9%	9.5%
0.3 x 0.3	7.9%	15.5%	24.9%	20.0%	31.1%	7.2%
0.5 x 0.5	6.9%	15.2%	24.1%	19.1%	30.6%	6.3%
1 x 1	6.0%	14.9%	23.5%	18.0%	29.6%	5.3%
2 x 2	5.4%	14.6%	21.2%	16.7%	27.2%	4.9%
4 x 4	4.5%	13.0%	18.3%	14.4%	25.6%	4.4%
7 x 7	3.7%	10.6%	14.5%	11.5%	24.7%	3.7%
11 x 11	3.1%	8.6%	11.7%	9.5%	25.3%	3.4%

DESERT ROCK						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMV
0.1 x 0.1	11.2%	16.4%	14.7%	14.9%	22.0%	10.5%
0.3 x 0.3	7.7%	14.2%	12.8%	11.6%	21.6%	7.2%
0.5 x 0.5	6.5%	13.8%	12.2%	10.7%	21.1%	6.0%
1 x 1	5.0%	13.8%	10.1%	8.9%	19.6%	4.7%
2 x 2	3.9%	12.8%	8.1%	6.8%	17.7%	4.0%
4 x 4	3.1%	11.8%	7.0%	5.6%	16.5%	3.6%
7 x 7	2.8%	10.1%	7.9%	6.4%	16.8%	3.6%
11 x 11	2.6%	7.4%	7.1%	5.4%	15.4%	3.1%

TABLE II
Day-Ahead MAPE Statistics

BONDVILLE						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMV
0.1 x 0.1	20.3%	20.6%	27.5%	24.6%	NA	NA
0.3 x 0.3	19.1%	19.8%	26.4%	23.3%	NA	NA
0.5 x 0.5	18.4%	19.2%	25.7%	22.5%	NA	NA
1 x 1	17.6%	18.5%	25.1%	21.7%	NA	NA
2 x 2	16.1%	17.2%	23.8%	19.8%	NA	NA
4 x 4	13.7%	15.3%	20.9%	16.8%	NA	NA
7 x 7	10.7%	12.8%	16.4%	13.2%	NA	NA
11 x 11	8.5%	9.8%	12.8%	10.5%	NA	NA

DESERT ROCK						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMV
0.1 x 0.1	13.8%	16.3%	13.4%	14.9%	NA	NA
0.3 x 0.3	10.5%	14.1%	11.2%	11.8%	NA	NA
0.5 x 0.5	9.6%	13.7%	10.8%	11.0%	NA	NA
1 x 1	7.9%	14.0%	8.7%	9.2%	NA	NA
2 x 2	6.1%	12.9%	6.9%	7.4%	NA	NA
4 x 4	4.9%	11.2%	5.8%	5.9%	NA	NA
7 x 7	5.3%	8.9%	7.4%	6.5%	NA	NA
11 x 11	4.5%	6.9%	7.1%	5.6%	NA	NA

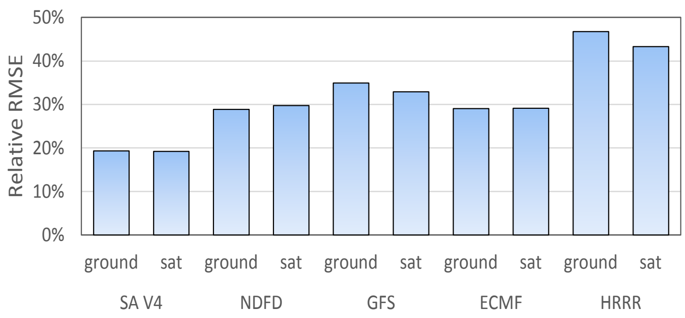

Fig. 1. Comparing single-point mean relative RMSE statistics for all models across all time horizons when using ground measurements vs. historical satellite data as a benchmark.

TABLE III
PERCENT PRODUCTION CURTAILED/BACKUP & CORRESPONDING ELECTRICITY STORAGE COST PER PV KW TO INSURE PERFECT DAY AHEAD FORECAST

footprint (degrees)	point	2 x 2	4 x 4	7 X 7
Desert Rock				
% curtailed & backup	7.88%	3.23%	2.46%	2.29%
Battery cost per PV kW	$385	$216	$128	$111
Bondville				
% curtailed & backup	7.21%	5.52%	4.65%	2.89%
Battery cost per PV kW	$317	$260	$209	$124

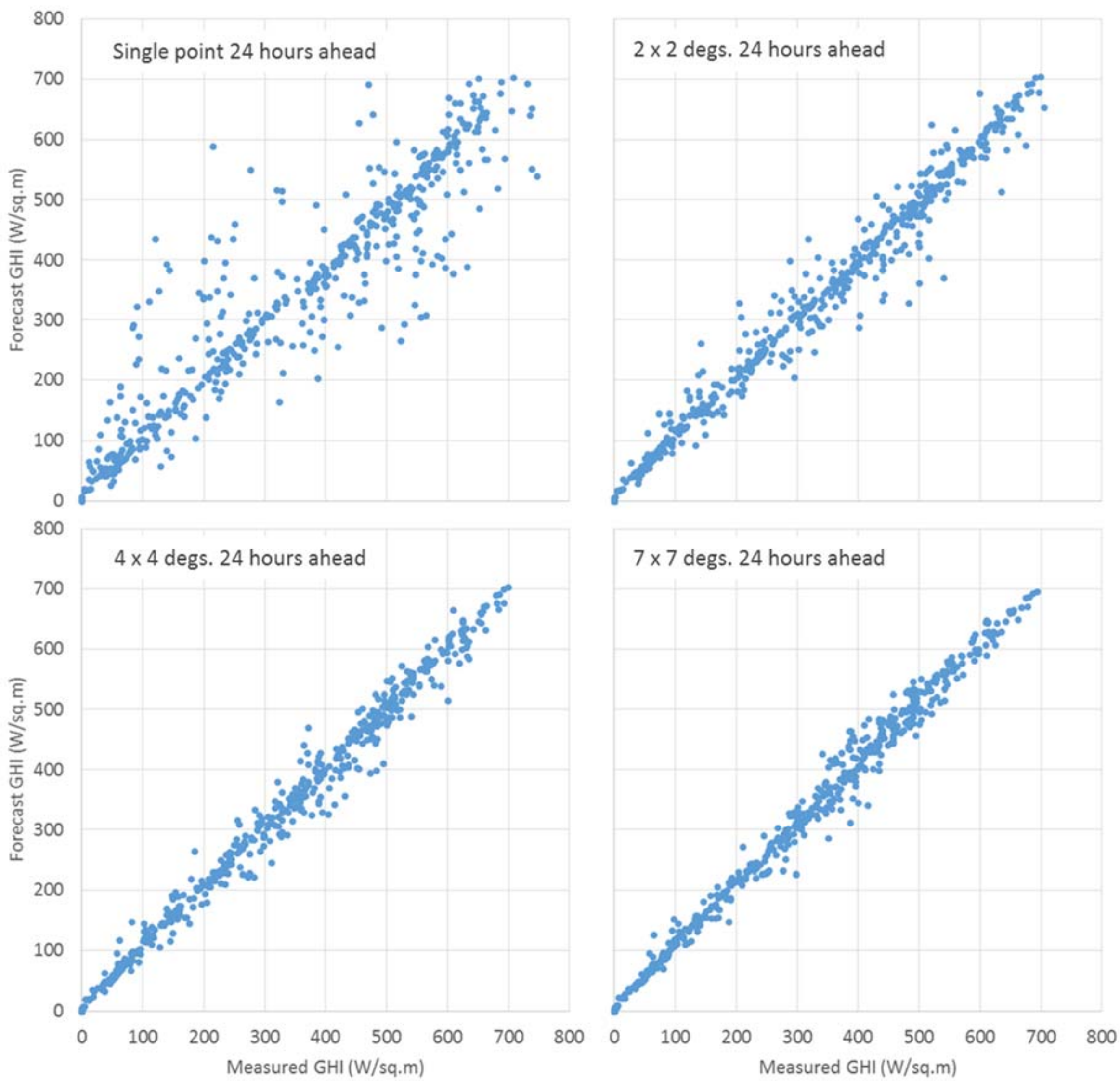

Fig. 2. Day Ahead SA-V4 Forecast vs. Actual GHI in the Southwestern US as a function of balancing area footprint