Perfect Operational Solar Forecasts: A Scalable Strategy toward Firm Power Generation

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Abstract

We present the *perfect forecast* concept as both an effective forecast validation metric and an operational strategy to integrate increasing amounts of variable solar power generation on power grids. The costs incurred in transforming imperfect into perfect predictions define the new metric: these include the costs of backup storage and output curtailment necessary to make-up for any over/under predictions. We illustrate the concept with the most recent version of the SUNY forecast model for hour-ahead and day-ahead forecast examples with single power plants as well as distributed PV fleets. We show that delivering perfect predictions – i.e., fully eliminating grid-operators uncertainty -- is achievable at small operational cost. Most importantly, we show that a perfect forecast strategy with optimized least-cost storage and overbuild/curtailment is an effective first step of a long-term strategy to cost-optimally transform variable PV generation into firm, effectively dispatchable generation capable of displacing conventional dispatchable and baseload generation.

Key-words: solar resource, irradiance, forecast, storage, high-penetration, firm power generation

1. Introduction

Solar power forecasts are an increasingly important part of utility and solar industry operations. Models are becoming more sophisticated and accurate (e.g., Blaga et al., 2019, Yang et al., 2018) and their further development and validation are the focus of several international collaborative efforts such as that piloted by the International Energy Agency PV Power Systems Task 16 (IEA, 2019). The authors have produced one such model -- often referred to as the SUNY model (Perez et al., 2018) -- that is operational in North America and served by the SolarAnywhere™ data service (SolarAnywhere, 2019). This service is used extensively by the solar and utility industries for both centralized PV plants and dispersed PV fleets production forecasts. The SUNY model is an optimized blend of satellite-based cloud motion vector (CMV) forecasts and operational regional/global numerical weather prediction (NWP) cloud cover and irradiance forecasts. The Electric Power Research Institute (EPRI) recently evaluated this state-of-the-art model in climatically diverse US regions, and found it to be most accurate among eleven other operational models (EPRI, 2017).

This paper contains two parts. The first part focuses on model validation and contrasts standard validation metrics (e.g., Mean Absolute Errors) to the new perfect forecast metric. The second part discusses the logistics of operational perfect forecasts and argues how such logistics could logically evolve toward least cost, ultra-high penetration of variable solar [and/or wind] power generation.

2. Forecast Model Evaluation

We analyze the latest version of the SUNY model (Perez et al., 2018) as well as its four underlying Numerical Weather Prediction (NWP) models: HRRR (2019), NDFD (2019), GFS (2019) and ECMWF (2019). In addition to these NWP models, the SUNY model blend includes satellite-derived cloud-motion-vector forecasts that are not evaluated here. The blend is a function of time horizon, solar geometry and predicted insolation conditions. The operational version of the SUNY model was independently evaluated and found to perform best among eleven US forecast providers (EPRI, 2017). Here, we evaluate a newer (beta) version that evolves the model's blend over time to locally capture the evolution of the relative performance of its underlying models.

All validations are fully independent. For the SUNY model, the validation data are entirely distinct from the data used for blend optimization.

We consider three logistically important time horizons: 1, 3, and 24 hours ahead.

We evaluate performance for seven point-specific locations as well as for a fleet of sixteen locations in California. The evaluation period spans 16 months from January 2016 to April 2017. Out of this period, we analyzed ~ 11.5 months' worth of data when all models were present.

For both point-specific and regional validations, we use global irradiance (GHI) as proxy for solar production.

The seven-station SURFRAD network that spans a wide range of climatic conditions (SURFRAD, 2019) is used for the site-specific validations. For the regional fleet validation we consider the aggregated output of 16 identical plants located in each of the state's climatic regions shown in figure 1 (CEC, 2017). The considered points are located at the barycenter of each region. We use SolarAnywhere satellite-derived historical irradiances for performance benchmarking (SolarAnywhere, 2019). We had previously shown that using satellite irradiances is acceptable, if not in many cases preferable, to validate forecasts, yielding error metrics comparable to ground measurement validations (Perez et al., 2016). In a recent article (Yang & Perez, 2019) we further discuss the appropriateness of satellite data for forecast validations: we show that while satellite data may be a suboptimal reference for single points (under-representing short-term variability) they are appropriate for intercomparing models, especially as the footprint evolves from single points (individual plants) to regions (PV fleets).

2.1 Standard Metrics

Commonly used standard metrics include Mean Bias, Mean Absolute and Root Mean Square errors (resp. MBE, MAE, RMSE) as well as their relative (percent) counterparts normalized either to the mean [daytime or 24-hour] observation or to nominal installed capacity. Another frequently used standard metric is the Forecast Skill that contrasts a model's RMSE to that of persistence. Several definitions of persistence exist, including: simple persistence of irradiance or power; scaled persistence of irradiance or power to account for [fully predictable] solar geometry variations; and more stringent definitions often termed "smart persistence" such as the one informally adopted by the IEA Task 46 experts (IEA, 2017). The latter consists of increasing the integration time defining current conditions commensurately to the forecast time horizon.

The choice of possible relative references for MBE, MAE and RMSE as well as the possible definitions of persistence do constitute a source of ambiguity when comparing published results from different studies, particularly for those who are not well versed in the metrics' definitions.

In this paper we focus on the often-preferred absolute MAE metric and the Forecast Skill in its IEA-Task 46 version (IEA, 2017). An advantage of the absolute MAE is that it can be easily interpreted in terms of %MAE normalized to nominal capacity conditions – here, since we use GHI as a proxy for PV power generation, the nominal percent error is obtained dividing the absolute MAE by 1,000 Wm^{-2} (plane of array irradiance at rated conditions)

Absolute MAEs for each of the SURFRAD sites and for the California fleet are reported in Table 1. Forecast skills for the same locations are reported in Table 2. A sample of the results in Table 1 and 2 are illustrated in Figures 2 and 3, respectively.

Tab. 1: Mean Absolute Errors for individual SURFRAD locations and for the 16-site California Fleet

Location	SUNY	Smart Persitence	GFS	NDFD	ECMWF	HRRR
One Hour Ahead MAE (Wm-2)						
GoodwinCreek	43	51	73	78	66	83
Boulder	61	58	79	90	76	81
Sioux Falls	50	44	67	81	63	78
Penn State	53	53	73	78	70	96
Fort peck	47	44	67	79	60	77
Desert Rock	39	39	46	50	43	62
Bondville	47	49	69	78	64	84
SURFRAD MEAN	**49**	**49**	**68**	**76**	**63**	**80**
California (Mean of indiv. Sites)	34	39	51	53	45	58
California Fleet	**12**	**17**	**25**	**30**	**19**	**30**
3 Hours Ahead MAE (Wm-2)						
GoodwinCreek	57	95	74	80	67	83
Boulder	68	108	79	90	75	86
Sioux Falls	55	86	69	83	63	83
Penn State	62	99	75	81	70	98
Fort peck	55	79	69	80	60	80
Desert Rock	43	73	48	52	44	64
Bondville	58	95	71	82	66	84
SURFRAD MEAN	**57**	**91**	**69**	**78**	**64**	**83**
California (Mean of indiv. Sites)	42	65	52	54	46	66
California Fleet	**16**	**37**	**26**	**31**	**20**	**35**
24 Hours Ahead MAE (Wm-2)						
GoodwinCreek	64	144	79	87	68	na
Boulder	77	122	83	96	78	na
Sioux Falls	66	130	72	84	70	na
Penn State	67	129	77	85	71	na
Fort peck	60	94	72	79	65	na
Desert Rock	47	89	50	55	47	na
Bondville	71	134	81	90	75	na
SURFRAD MEAN	**64**	**120**	**73**	**82**	**68**	**na**
California (Mean of indiv. Sites)	46	87	53	57	46	na
California Fleet	**19**	**60**	**27**	**32**	**20**	**na**

These evaluation results are consistent with our previous publications (e.g., Perez et al., 2018), with ECMWF exhibiting the best performance among the underlying NWP models, followed by GFS, NDFD and HRRR. The SUNY model is well ahead of the NWPs for short time horizons – thanks to the advantage provided by its satellite cloud motion component -- and slightly better than ECMF -- its major blend component -- for longer time horizons.

The California fleet exhibits considerably reduced MAEs compared to individual sites. Whereas individual points in California are comparable to Desert Rock (see the individual location California mean of individual sites in Table 1), the fleet's MAE is reduced by a factor of nearly 3 for the SUNY model, achieving 12 Wm^{-2} for 1 hour ahead and 19 Wm^{-2} for 24 hours ahead (i.e., respectively 1.2% and 1.9% of installed capacity)

Results for the forecast skill metric are also consistent with our previous findings: the underlying NWP models exhibit a negative skill for one hour ahead while skills become positives beyond 3-hour time horizons. The SUNY model exhibits a positive skill for all horizons, reaching over 40% for 24 hours ahead forecasts. Interestingly, the skill differential between the models is noticeably amplified for the regional fleet compared to individual locations: higher skill for the best models (SUNY is 66% for 24 hours ahead), lower skill for worst models.

Tab. 2: Forecast Skills for individual SURFRAD locations and for the 16-site California Fleet

FORECAST SKILL	SUNY	GFS	NDFD	ECMWF	HRRR
One Hour Ahead					
GoodwinCreek	23%	-43%	-41%	-17%	-61%
Boulder	4%	-37%	-36%	-19%	-34%
Sioux Falls	-1%	-55%	-69%	-32%	-79%
Penn State	8%	-28%	-40%	-19%	-68%
Fort peck	4%	-52%	-68%	-31%	-71%
Desert Rock	12%	-18%	-18%	-3%	-55%
Bondville	4%	-40%	-59%	-30%	-69%
SURFRAD MEAN	**8%**	**-39%**	**-46%**	**-21%**	**-61%**
California Mean (single locations)	21%	-25%	-33%	-4%	-44%
California Fleet	**21%**	**-46%**	**-113%**	**-22%**	**-118%**
3 Hours Ahead					
GoodwinCreek	37%	13%	13%	29%	3%
Boulder	36%	17%	18%	29%	15%
Sioux Falls	35%	11%	4%	26%	-5%
Penn State	38%	23%	14%	30%	-1%
Fort peck	33%	8%	0%	22%	-5%
Desert Rock	35%	21%	21%	33%	-6%
Bondville	39%	19%	8%	31%	5%
SURFRAD MEAN	**36%**	**16%**	**11%**	**29%**	**2%**
California Mean	33%	11%	6%	27%	-16%
California Fleet	**54%**	**33%**	**4%**	**45%**	**-26%**
24 Hours Ahead					
GoodwinCreek	48%	33%	30%	46%	na
Boulder	32%	17%	15%	29%	na
Sioux Falls	45%	35%	30%	41%	na
Penn State	44%	32%	24%	40%	na
Fort peck	35%	15%	14%	27%	na
Desert Rock	41%	32%	30%	39%	na
Bondville	41%	29%	25%	37%	na
SURFRAD MEAN	**41%**	**28%**	**24%**	**38%**	**na**
California Mean	41%	26%	20%	38%	na
California Fleet	**66%**	**55%**	**34%**	**64%**	**na**

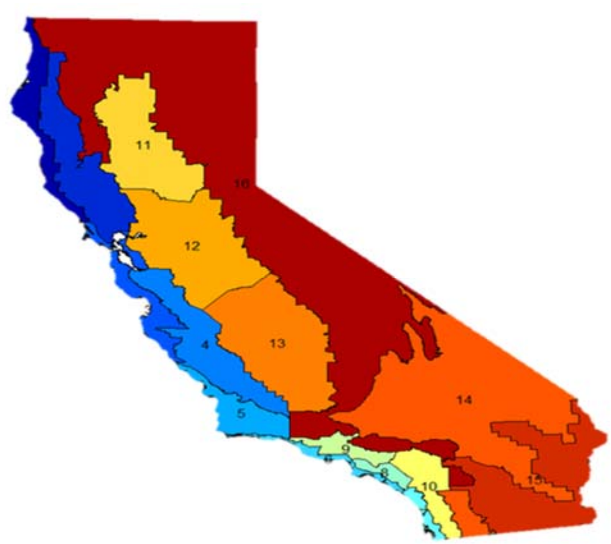

Fig. 1: Sixteen California Climatic Regions

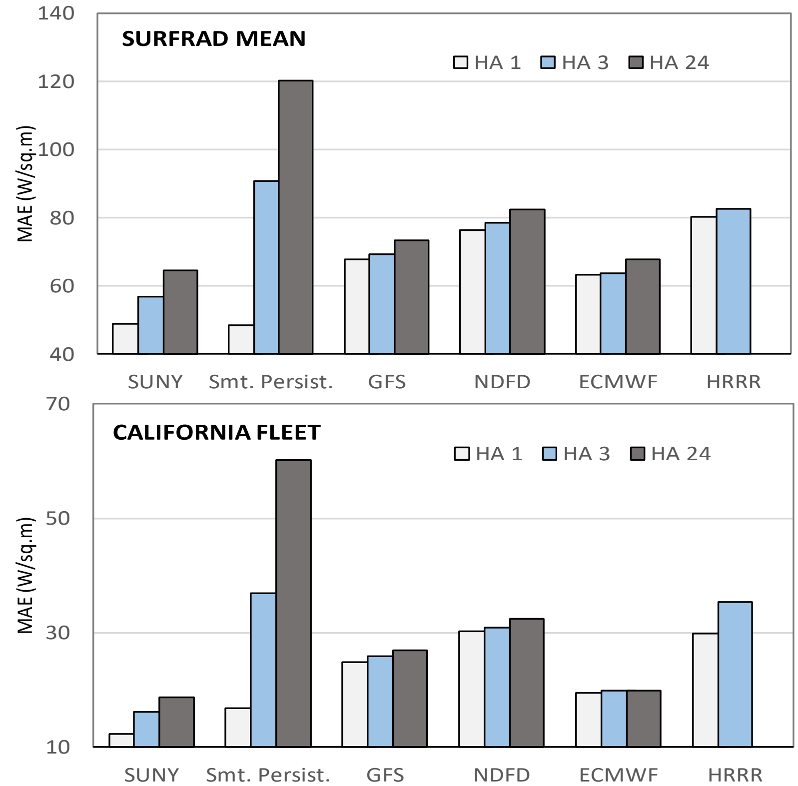

Fig. 2. Mean Absolute Errors for the individual SURFRAD stations (top) and for the California Fleet (bottom.)

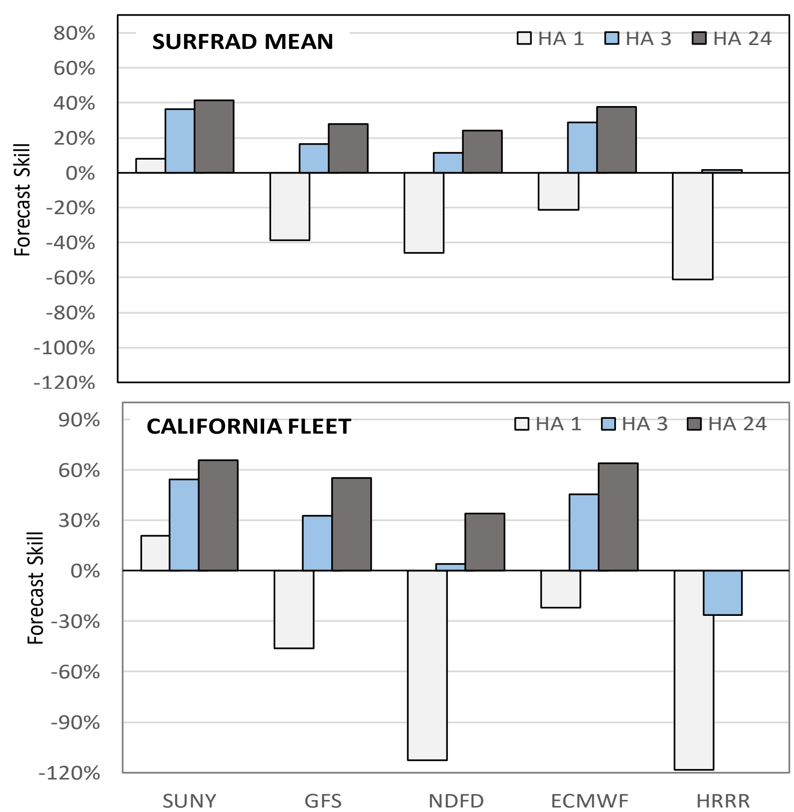

Fig. 3. Mean forecast skill for individual SURFRAD locations (top) and for the California Fleet (bottom)

2.2 Perfect Forecast Metric

In a previous article, we had introduced an initial version of this metric: the cost of storage necessary to offset any over-predictions (Perez et al., 2016). This initial definition allowed nighttime storage recharge (i.e., implying low demand and low-cost electricity available at night).

The metric we apply in this article derives from an operationally more robust strategy built on a new algorithm to transform intermittent PV or wind generation into firm production at lowest cost (Perez et al., 2019a, Perez, 2014): this algorithm seeks the optimum (least-cost) combination of storage and PV oversizing to meet a specified load profile with 100% certainty. This optimum combination depends on the relative costs of storage and PV. Here we consider two scenarios for these costs:

(1) a current utility-scale scenario with turnkey PV at $1,200 per kWac and storage at $200/kWh of storage capacity;
(2) a future (2050) utility-scale scenario with PV at $400 per kWac and storage at $50/kWh.

The perfect forecast metric can either be expressed in terms of additional $/kW above and beyond the cost of unconstrained PV, or in terms of levelized cost of energy (LCOE) premium above and beyond the LCOE of unconstrained PV. Note that LCOE metric requires additional inputs -- the weighted average cost of capital (WACC) and operating costs, in particular – hence our choice of $/KW for the present paper.

Results are presented in Table 3, for two sample SURFRAD locations and for the 16-points California Fleet.

Tab. 3: Perfect Forecast $/kW premium for selected SURFRAD locations and for the 16-site California Fleet

PERFECT FORECAST METRIC	SUNY	Smart Persitence	GFS	NDFD	ECMWF	HRRR
One Hour Ahead Perfect Forecast Metric ($/kW -- current)						
Goodwin Creek	$ 414	$ 182	$ 1,145	$ 1,441	$ 1,281	$ 2,330
Desert Rock	$ 398	$ 161	$ 968	$ 898	$ 692	$ 1,197
California Fleet	**$ 118**	**$ 89**	**$ 285**	**$ 169**	**$ 246**	**$ 595**
One Hour Ahead Perfect Forecast Metric ($/kW -- future)						
Goodwin Creek	$ 115	$ 47	$ 328	$ 365	$ 343	$ 627
Desert Rock	$ 110	$ 44	$ 261	$ 234	$ 192	$ 328
California Fleet	**$ 33**	**$ 23**	**$ 77**	**$ 50**	**$ 69**	**$ 163**
3 Hours Ahead Perfect Forecast Metric ($/kW -- current)						
Goodwin Creek	$ 589	$ 489	$ 1,180	$ 764	$ 892	$ 2,166
Desert Rock	$ 560	$ 434	$ 1,017	$ 912	$ 691	$ 1,076
California Fleet	**$ 172**	**$ 255**	**$ 316**	**$ 184**	**$ 262**	**$ 629**
3 Hours Ahead Perfect Forecast Metric ($/kW -- future)						
Goodwin Creek	$ 164	$ 130	$ 339	$ 220	$ 251	$ 567
Desert Rock	$ 149	$ 111	$ 275	$ 237	$ 191	$ 291
California Fleet	**$ 47**	**$ 71**	**$ 86**	**$ 54**	**$ 77**	**$ 173**
24 Hours Ahead Perfect Forecast Metric ($/kW -- current)						
Goodwin Creek	$ 835	$ 1,645	$ 1,234	$ 949	$ 1,016	na
Desert Rock	$ 711	$ 1,208	$ 1,166	$ 1,203	$ 772	na
California Fleet	**$ 199**	**$ 629**	**$ 441**	**$ 363**	**$ 224**	**na**
24 Hours Ahead Perfect Forecast Metric ($/kW -- future)						
Goodwin Creek	$ 227	$ 419	$ 356	$ 266	$ 277	na
Desert Rock	$ 189	$ 309	$ 309	$ 308	$ 205	na
California Fleet	**$ 52**	**$ 177**	**$ 115**	**$ 96**	**$ 62**	**na**

The perfect forecast metric results are interesting on two fronts.

First on the operational front, delivering perfect 24-hour forecasts for the 16-plant fleet can be achieved for less than \$200/kWp at current hardware cost. This will reduce to ~ \$50/kW with anticipated future PV/Storage costs. Perfect forecast thus amount to a small financial burden to guarantee operational certainty for the TSOs.

Second, on the accuracy metric front, we note that the model performance ranking is different from the ranking inferred from standard metrics. Particularly noteworthy is the better performance of persistence in relation to the underlying NWPs when benchmarked with the perfect forecast instead of the MAE metric. This ranking difference is illustrated in Figure 4. In this figure, the relative performance of each model is gauged against the average performance of all the model models across all considered locations and time horizons – a relative performance below 100% is better than the mean, and vice versa. Whereas persistence scores poorly when using the standard MAE as a metric, it bests the reference NWPs when using the perfect forecast metric. The optimally blended SUNY model scores very well with both metrics.

This observed ranking difference between the two metrics can be explained as follow: whereas the MAE is driven by the error of individual (hourly) forecast events, the perfect forecast metric is driven by the accumulation of under- or over-forecast conditions that determine the amount of storage and the degree of plant oversizing. The persistence model is better 'balanced' in this respect, with shorter periods of enduring over/underpredicted conditions than the reference NWPS.

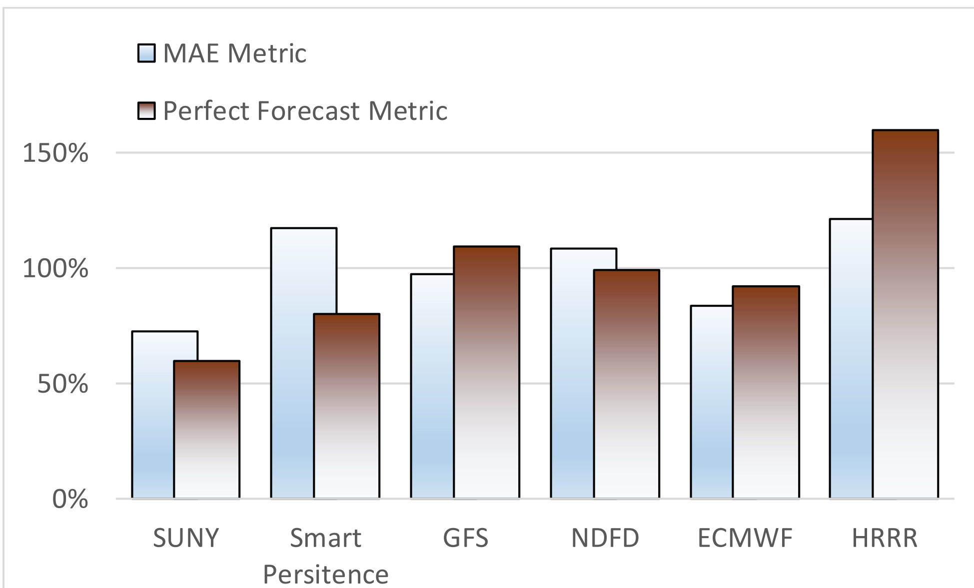

Fig. 4. Comparing model performance ranking across all locations and time horizons for standard and perfect forecast metrics. The value of 100% amounts to the mean error metric of all models/locations/time-horizons.

3. A Scalable Strategy toward Firm Power Generation

As discussed above, perfect forecasts constitute an economically attractive operational strategy for both grid operators and solar operators. For grid operators, perfect operational forecasts remove all supply-side load imbalance uncertainty and associated costs (e.g., spinning reserves) from intermittent renewable energy resources like PV or wind. For producers, perfect forecast operations amount to replacing imperfect administrative/regulatory penalties – that can evolve rapidly overtime -- by modest, predictable tangible hardware costs (PV overbuild and battery).

However, the real value of a perfect forecast strategy lies in its operational scalability to least-cost firm, effectively dispatchable PV (or wind) power generation. Firm PV power generation -- i.e., the capability of meeting grid demand 24/7 year-around regardless of time of day, time of year and weather conditions -- is a prerequisite to ultra-high PV penetration and the displacing of conventional baseload and dispatchable resources.

The landmark Minnesota Solar Pathway study (Perez et al., 2019a, MN Dept. of Commerce, 2018, Perez & Rabago, 2019) demonstrated that the least-cost means of transforming intermittent renewable energy resources (wind and PV) into firm, effectively dispatchable resources entails optimizing generation oversizing and storage reserves. The results of this project show that firm power generation is achievable in a northern state at costs near or below current conventional generation costs – even before accounting for any environmental benefits (Perez et al. 2019a, Perez et al., 2019b). Figure 5 (from Perez et al., 2019b) illustrates the case of meeting the Minnesota's transmission operator (MISO) load with 100% certainty, using an optimized mix of wind and solar resources and allowing for a maximum amount natural gas generation of 5%. The figure assumes utility-scale PV wind and battery future cost projections.

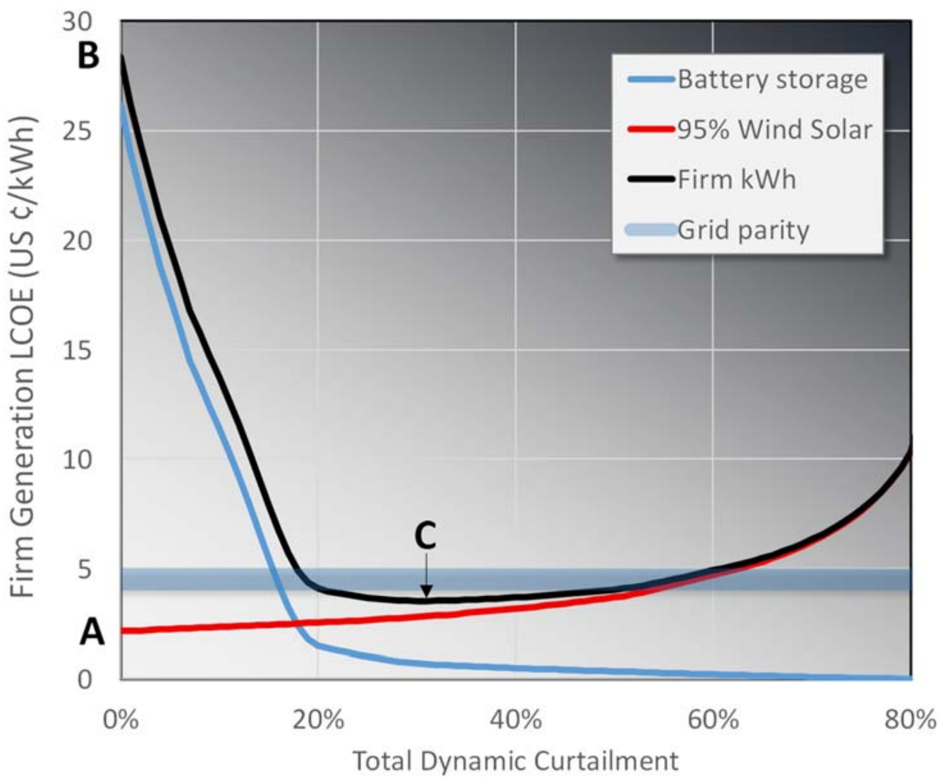

Fig. 5. Illustrating the catalyst role of overbuilding/curtailment in achieving firm least-cost power generation. Without overbuilding/curtailment, unconstrained variable wind/solar electricity will certainly achieve [apparent] grid parity (A). However transforming this variable renewable generation in effectively dispatchable firm power generation capable of meeting demand 100% of the time will remain well in excess of grid parity if overbuilding/curtailment is avoided because of the quantity of storage required to make up for multi-day and seasonal production gaps (B). With optimally overbuilt renewables, storage requirements can be reduced to the point where firm renewable power generation can achieve real grid parity (C), hence effectively displace conventional power generation (source: Perez et al., 2019b)

Importantly, the operational logistics of least-cost dispatchable PV generation –optimized overbuilding and storage associated with PV overbuild and proactive operational curtailment -- are identical to the logistics of delivering perfect forecasts, but on a larger scale (i.e., more storage and overbuilding/curtailment).

Therefore, an operational perfect forecasts strategy constitutes a low-expense entry-level step and a learning curve for both grid operators and energy producers toward enabling large-scale dispatchable PV power generation capable of meeting load demand 24/7/365.

The transition from perfect forecast to fully dispatchable PV can be gradual over time following grid operators' learning curve, PV penetration, and storage/PV costs decreases. Figure 6 graphically contrasts the tasks for meeting perfect forecast and firm power generation objectives over a sample 10-day period. While the firm power generation task is considerably heavier, both involve a transformation of the unconstrained solar resource into a predicted output: predicted production in the case of perfect forecast, and load shape in the case of firm power generation. Both involve an optimization of storage and overbuild/curtailment requirements.

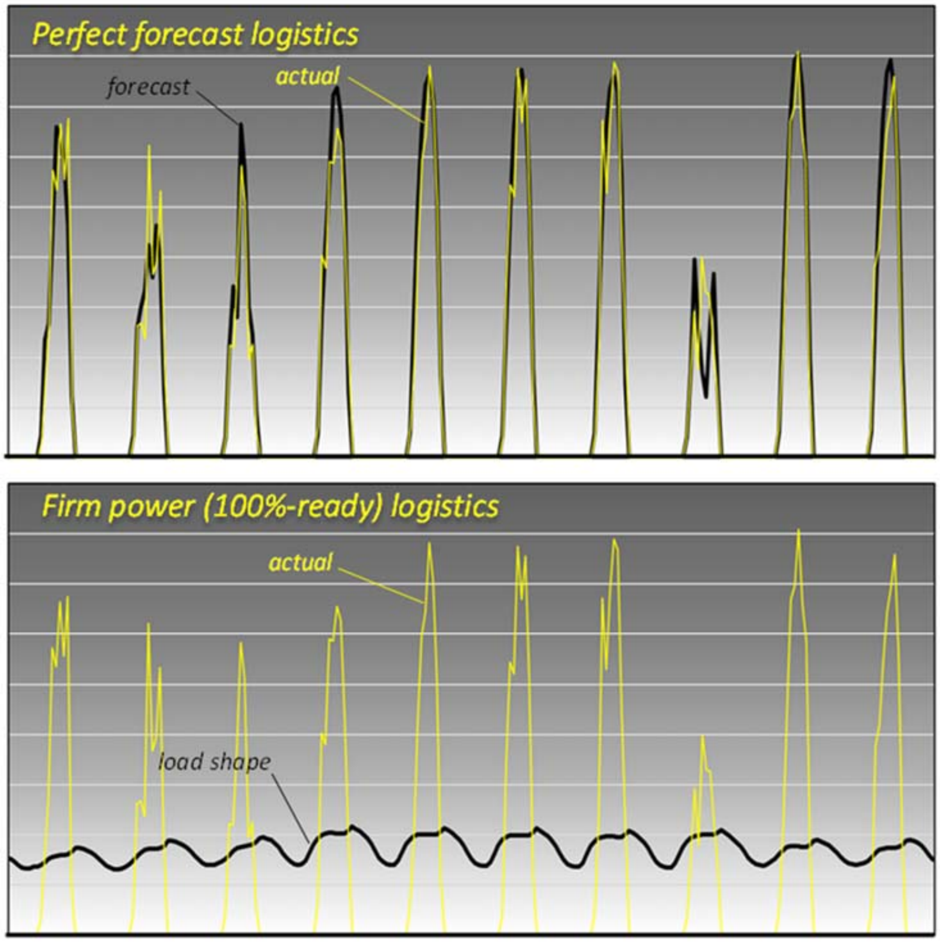

Fig. 6. Comparing the perfect forecast task of transforming PV output into predicted PV output (top) to the firm power generation task of transforming PV output into the grid's load shape (bottom).

In Figure 7, we illustrates how a gradual transition from perfect forecast to firm power generation could logically occur. The figure shows the same 10 days' worth of forecasted PV production (black line) and the regional TSO load shape (red line). A gradual transition from perfect forecast logistics (guaranteed output = forecast) to firm power generation logistics (guaranteed output = regional load) could occur progressively as PV penetration increases while keeping the same operational storage/curtailment control logistics, in effect moving from the optimum storage/curtailment cost reported in Table 3, to the optimum firm power generation cost illustrated in Figure 5.

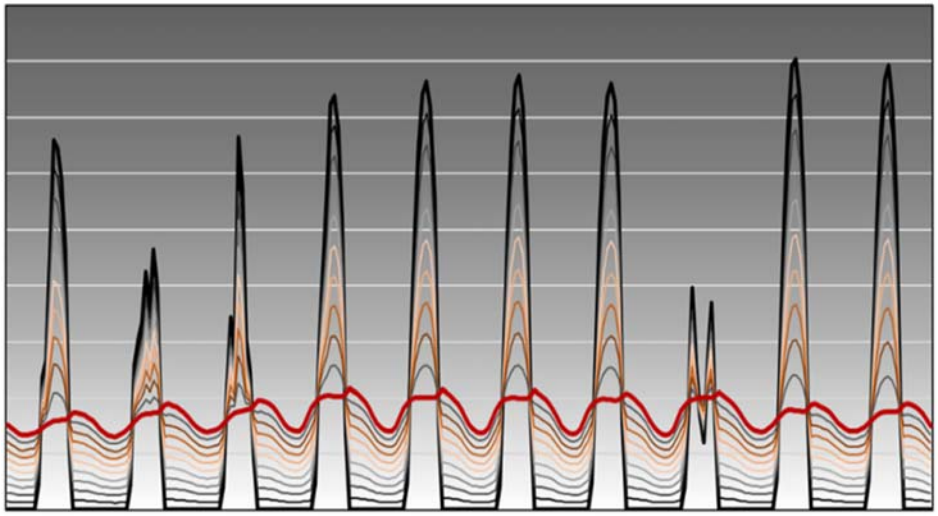

Fig. 7. Illustrating a gradual transition from a perfect forecast PV target (black line) to a regional load demand profile target (red line).

4. Conclusions

Perfectly forecasting PV production as defined in this article amounts to guaranteeing [imperfectly] forecasted production by: (1) optimally overbuilding[1] the PV resource to allow curtailment, and (2) operating optimally sized battery storage in parallel with PV.

The perfect forecast concept is innovative and effective in three respects:

- As a metric, it offers unique insights on model performance that are directly relevant to the logistical costs of operating PV fleets on a power grid. We showed that, compared to standard error metrics, the perfect forecast metric led to different conclusions regarding the comparative performance of different models. In particular, the perfect forecast metric indicates that smart persistence is a considerably more robust model than a standard metrics assessment would indicate.
- Perfect forecasts represent an operational strategy for grid operators and producers alike that can entirely remove supply-side load imbalance uncertainty from intermittent renewable energy production.
- Finally, and most importantly, perfect forecast operations represent an actionable entry step to optimally achieve least cost ultra-high PV (or wind) penetration.

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[1] Note that this could also may be achieved by under-predicting forecasts instead of overbuilding plants.

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