A Concise Overview on State-of-the-Art Solar Resourcing and Forecasting

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Jan Kleissl

Jan Kleissl researches the interaction of weather with engineering systems in solar power systems and the electric power grid. Kleissl received an undergraduate degree from the University of Stuttgart and a PhD from the Johns Hopkins University, both in environmental engineering with a focus in environmental fluid mechanics. He is the Director of the UC San Diego Center for Energy Research and Professor in the Department of Mechanical and Aerospace Engineering at UC San Diego.

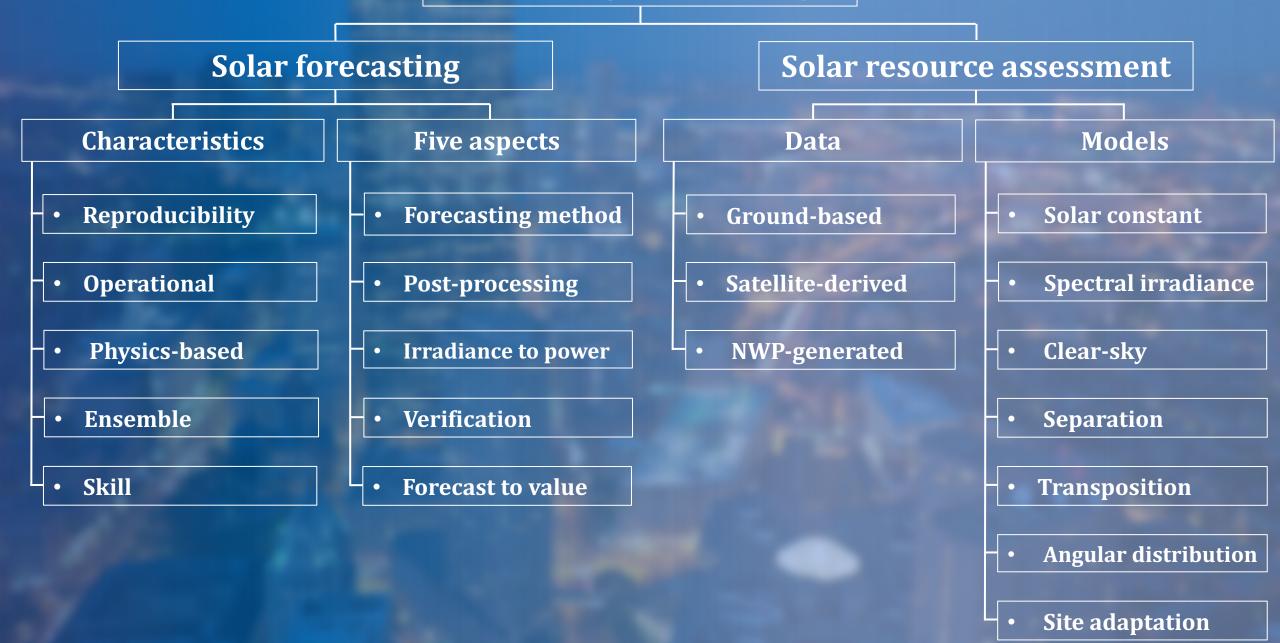


Dazhi Yang (杨大智)

He received his B.Eng., M.Sc., and Ph.D. degrees from the National University of Singapore in 2009, 2012, and 2015, respectively. Currently, he is a Professor with the School of Electrical Engineering and Automation, **Harbin Institute of Technology**. He has a profound interest in solar resource assessment, forecasting, and grid integration. He has been the youngest associate editor of the **Solar Energy** journal, which has 65 years of history, and since 2019, he has been one of the four Subject Editors of that journal. In the past decade, he authored more than **100 journal papers**, with a total citation of 4400, and an H-index of 36. In 2020, he has been identified as one of the **world's top 2% scientists** by Stanford University.



Solar energy meteorology



DATA FOR FORECASTING

SOLAR RESOURCE ASSESSMENT – GROUND DATA

/ Data for solar resource assessment

Ground-based measurements:

Radiometers

Different pyranometers and pyrheliometers are subject to different measurement uncertainties and performance.

High cost of research-grade radiometers

Operations and maintenance cost.

> Quality control (QC)

Ensure that the baseline for any subsequent validation is legitimate.

Four types of radiometry measurements:

- Global horizontal irradiance (GHI)
- Beam normal irradiance (BNI)
- Diffuse horizontal irradiance (DHI)
- Global tilted irradiance (GTI)

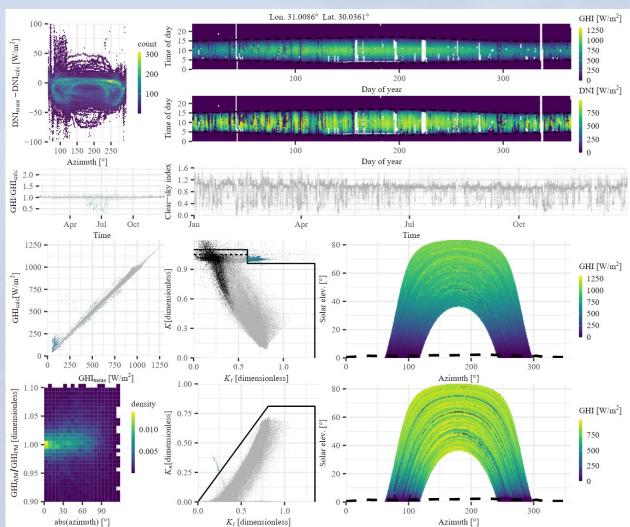


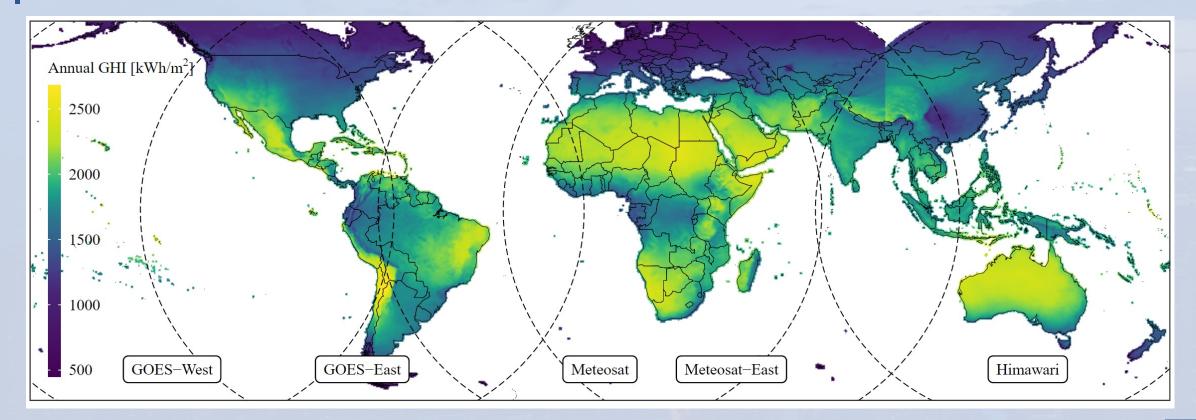
FIG. VISUALIZATION TO FACILITATE QUALITY CONTROL OF IRRADIANCE

SOLAR RESOURCE ASSESSMENT – SATELLITE DATA

/ Data for solar resource assessment

Satellite-derived irradiance data:

FIG. FIVE GEOSTATIONARY WEATHER SATELLITES JOINTLY COVER ALL LOCATIONS ON EARTH BETWEEN +60° AND -60° LATITUDE.



SOLAR RESOURCE ASSESSMENT – WEATHER MODEL

/ Data for solar resource assessment

Output of NWP models:

Forecasts a few times a day, over forecast horizons of a few days, at a regional or global scale.

> Forecast

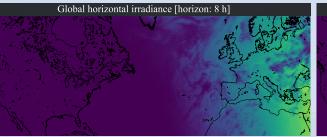
Operational models constantly undergo development.

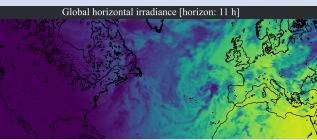
➢ Reanalysis

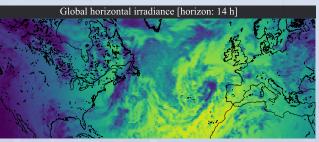
In contrast, reanalyses use "frozen" models and produce estimates of weather variables over a period typically spanning a few decades. For example:

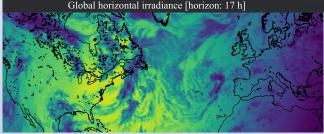
- <u>ECMWF Reanalysis, Version 5 (ERA5)</u>
- <u>Modern-Era Retrospective Analysis for Research and</u>
 <u>Applications, Version 2 (MERRA-2)</u>

FIG. VISUALIZATION OF ECMWF GHI FORECAST; NAM DOMAIN; MODIS AOD





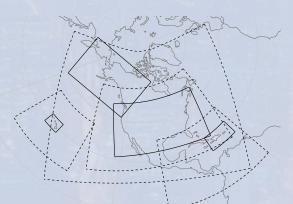


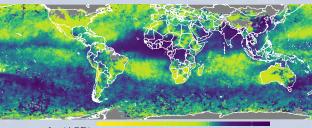


GHI [W/m²]

500

1000





 $\log(AOD)$ -6 -4 -2 0

SOLAR FORECASTING CHARACTERISTICS

SOLAR FORECASTING – CHARACTERISTICS

/ Salient characteristics of solar forecasting

The acronym of "ROPES":

• <u>Reproducibility</u>

- Falsifiability is an essential feature of scientific progress.
- Reproduction solely based on textual description is cumbersome.
- Instant reproducibility through data and code as supplementary materials.

Operational

- Forecast submission guidelines.
- Time parameters: forecast lead time, forecast horizon, forecast resolution, forecast refresh rate.

<u>P</u>hysics-based

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- Camera, satellite and NWP to produce initial forecasts.
- Post-process physics-based forecasts with machine learning.

<u>E</u>nsemble

- Dynamical ensemble (meteorology)
- Combining forecasts (statistics)
- Ensemble learning (computer science)

<u>S</u>kill

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Benchmark against reference and "perfect" forecast:

•
$$S = (A_f - A_r)/(A_p - A_r)$$

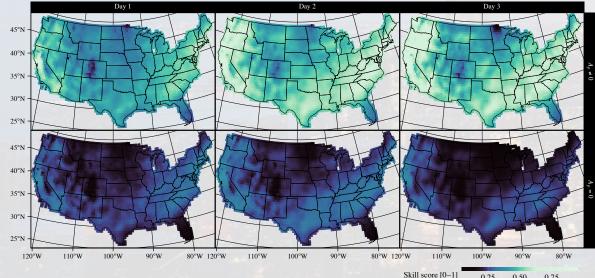
Predictability

SOLAR FORECASTING – SKILL

/ Five aspects of solar forecasting research

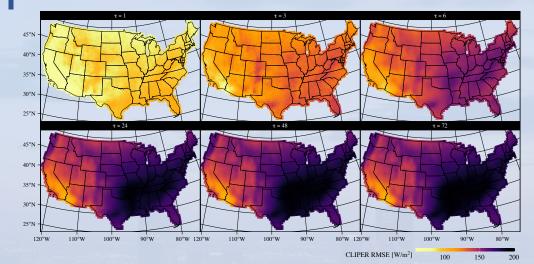
Skill 0

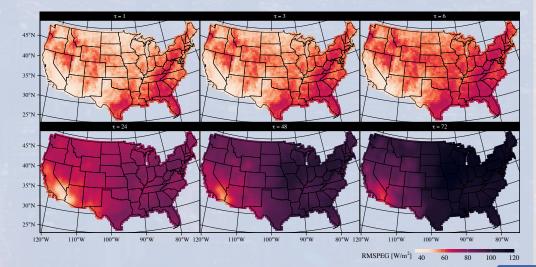
- $\succ S = \frac{A_f A_r}{A_p A_r}$
 - \succ A_r comes from CLIPER (optimal convex combination of climatology and persistence)
 - $> A_p$ comes from predictability error growth (the difference between a controlled run and a perturbed run)



0.25 0.50 0.75

FIG. CLIPER RMSE and predictability error growth





SOLAR FORECASTING RESEARCH THRUSTS

SOLAR FORECASTING – TYPES AND VERIFICATION

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/ Five aspects of solar forecasting research

• <u>B</u>ase methods

- Camera
- Satellite
- NWP

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<u>P</u>ost-processing

- Improve accuracy (D2D)
- Uncertainty quantification (D2P)
- Elicit forecast (P2D)
- Improve calibration (P2P)

<u>I</u>rradiance-to-power

- Direct (regression)
- Indirect (model chain)
- Hybrid (solar modeling up to effective irradiance + machine learning for the rest)

Verification

- Deterministic (Yang et al., 2020)
- Probabilistic (Lauret et al., 2019)

<u>M</u>aterialization of value

Grid-integration forecast penalty

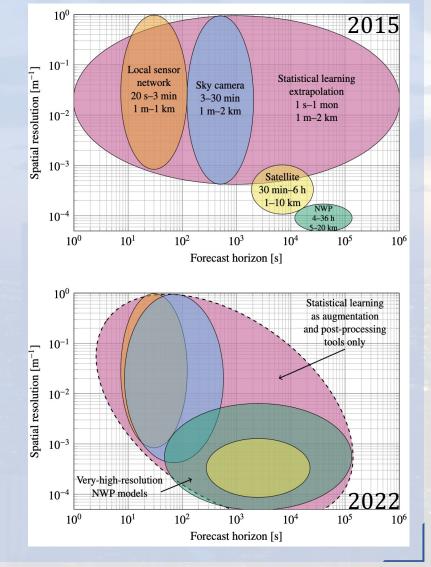
SOLAR FORECASTING – COMBINATION OF METHODS

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• Forecast methods

- Association between data source and forecast horizon has weakened
- Most advanced methods use more than one data source
 - 15-min, 3-km NWP
 - 5-min, 2-km satellite

FIG. HISTORICAL AND CURRENT PERSPECTIVE ON CATEGORIZATION OF FORECASTING METHODS

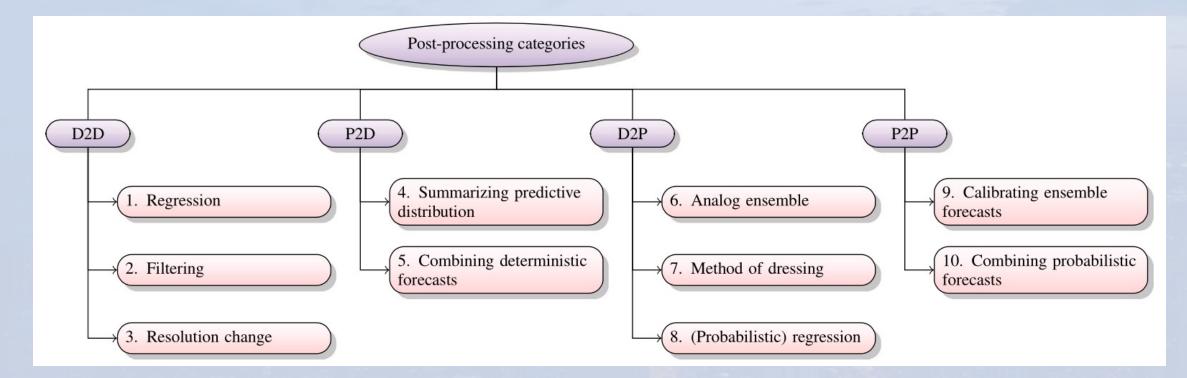


SOLAR FORECASTING – POSTPROCESSING

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• **Post-processing**

FIG. A complete typology of solar forecast post-processing



SOLAR FORECASTING – IRRADIANCE TO POWER

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• Irradiance-to-power conversion

Indirect approach considers explicitly the physics of different steps of the conversion, which include

- solar positioning
- separation and transposition modeling
- PV cell temperature modeling
- soiling, shading, mismatch
- degradation

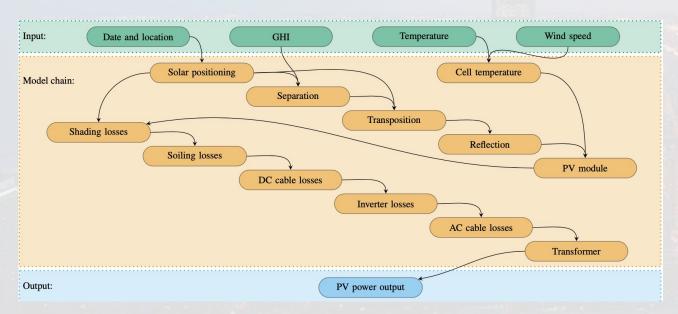
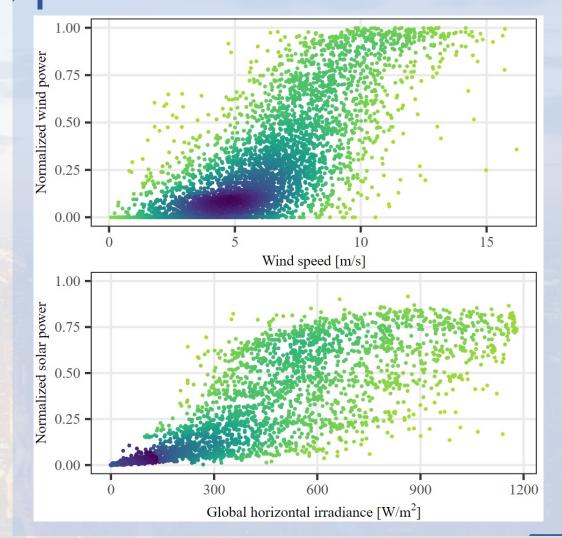


FIG. A TYPICAL WIND/SOLAR POWER CURVE



SOLAR FORECASTING – SEPARATION MODEL

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• Irradiance-to-power conversion

Separation model:

> Yang 4

Yang, D. (2022). Estimating 1-min beam and diffuse irradiance from the global irradiance: A review and an extensive worldwide comparison of latest separation models at 126 stations. Renewable and Sustainable Energy Reviews, 159, 112195. FIG. Worldwide validation of separation models (a) Location of 126 test stations

 Copen-Gener climate classification

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(b) Linear ranking for model performance

Model	Site				Mean rank	
	1	2	3		126	
Engerer2	4	1	6		6	4.32
Engerer4	7	6	7		8	6.68
Starke1	3	5	2		3	3.00
Starke2	5	8	3		2	5.04
Starke3	2	4	4		1	3.01
Abreu	8	7	8		7	7.87
PAULESCU	6	2	5		5	4.67
Every1	10	9	9		9	9.10
Every2	9	10	10		10	8.84
Yang4	1	3	1		4	2.47

SOLAR FORECASTING – TRANSPOSITION MODEL

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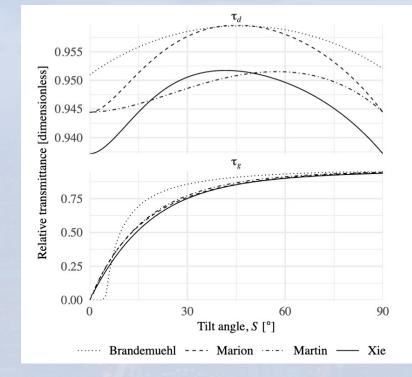
• Irradiance-to-power conversion

Transposition model:

Perez model

Angle-of-incidence (AOI) models:

- > Brandemuehl & Beckman 1980 (empirical)
- Martin & Ruiz 2001 (empirical)
- Marion 2017 (physical, numeric integration)
- > Xie et al. 2022 (physical, analytic solution)



- AOI modifier for beam component (τ_b) has always been known: Snell's law and Fresnel equation.
- AOI modifier for diffuse and ground-reflected components (τ_d and τ_g) have no analytic form
- Xie et al. derived an analytical form based on the Fresnel equation.

FIG. Latest advance in angle-of-incidence modeling

SOLAR FORECASTING – DC MODELS

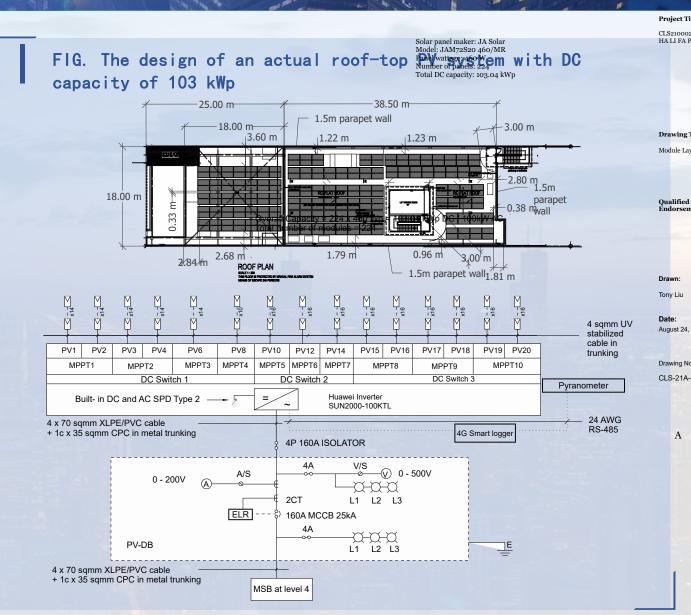
/ Five aspects of solar forecasting research

• Irradiance-to-power conversion

DC models:

- Surrogate versus detailed modeling
- How often do we have system design information?
- What is the difference between one-diode model and the PVWatts model

$$P_{\rm dc} = P_{\rm dc,mpp,ref} \frac{G_c'}{1000 \text{ W/m}^2} \left[1 + \gamma (T_{\rm cell} - 25^{\circ} \text{C}) \right]$$



SOLAR FORECASTING – VERIFICATION AND VALUE

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• Forecast verification

Consistency, quality, and value

Materialization of values

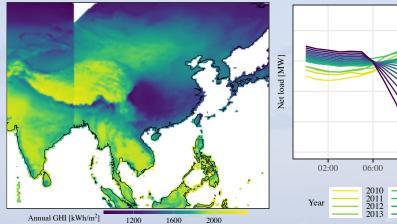
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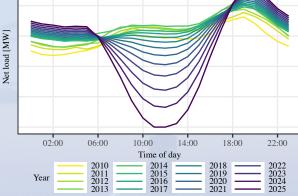
Examine the value of forecasts based on the time scale, the spatial domain, and the market for which the forecasts are produced.

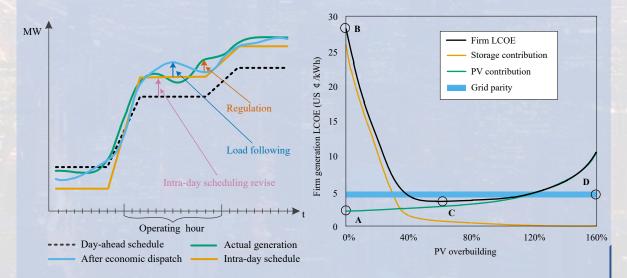
"First, it should be understood that forecasts possess <u>no intrinsic</u> <u>value</u>. They acquire value through their ability to <u>influence the</u> <u>decisions</u> made by users of the forecasts."

--Allan Murphy

FIG. SOME CONSIDERATION FOR GRID INTEGRATION







SOLAR FORECASTING – VALUE / PENALTY EXAMPLE

/ Five aspects of solar forecasting research

• **Post-Processing Probabilistic Forecasts**

4 Chinese grid operators with different penalty triggers and penalty equations.

How to post-process dynamical ensemble forecasts into highest-value deterministic forecast?

Scoring Functions

Using the appropriate scoring functions can reduce forecast error by O(a few %), occasionally more.

TAB. PENALTY TERMS FOR 4 CHINESE GRID OPERATORS

zone	penalty trigger [dimensionless]	penalty [¥]	scoring function	consistent functional
CCG	$E = \frac{1}{96} \sum_{t=1}^{96} \frac{ x_t - y_t }{Cap} > 15\%$	$(E - 15\%) \times \text{Cap}[\text{MW}] \times 1.5[\text{h}] \times p^{\text{avg}}[\text{¥/MWh}]$	AE	median
CSG	$E = \frac{1}{\text{Cap}} \sqrt{\frac{1}{96} \sum_{t=1}^{96} (x_t - y_t)^2} > 15\%$	$(E - 15\%) \times \text{Cap}[\text{MW}] \times 1[\text{h}] \times p^{\text{avg}}[\text{¥/MWh}]$	SE	mean
ECG	$E = \sqrt{\frac{1}{96} \sum_{t=1}^{96} \left(\frac{x_t - y_t}{y_t}\right)^2} > 20\%$	$(E-20\%) \times \text{Cap}[\text{MW}] \times 0.1[\text{h}] \times \alpha \times p^{\text{max}}[\texttt{¥}/\text{MWh}]$	SPE	$med^{(-2)}$
NEG	$E = \max\left(\left \frac{x_t - y_t}{x_t}\right \right) > 15\%, t = 1, \cdots, 96$	$\begin{cases} \int (1.15x_t - y_t dt[MWh] \times 100[\Psi/MWh] & \text{if } 1.15x_t < y_t \\ \int (0.85x_t - y_t dt[MWh] \times 100[\Psi/MWh] & \text{if } 0.85x_t > y_t \end{cases}$	RE	med ⁽¹⁾

TAB. 4 TYPES OF FORECAST ERRORS ASSOCIATED WITH USING DIFFERENT SCORING FUNCTIONS

Stn.	Scheme	RMSE	MAE	MRE	RMSPE
BON	mean	111.3	74.2	26.9	120.9
	median	113.1	73.5	26.9	120.9
	$med^{(1)}$	116.5	75.9	26.0	133.3
	$med^{(-2)}$	121.5	77.1	64.0	89.5
DRA	mean	75.9	47.5	13.3	58.5
	median	76.5	47.1	13.2	58.4
	$med^{(1)}$	76.5	47.5	12.9	62.6
	$med^{(-2)}$	82.6	49.6	19.2	49.4

FIRM PV POWER

FIRM PV POWER ENABLERS

Firm PV Power Enablers

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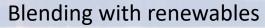
- □ Alleviate the volatility of PV power
- PV power can be thought of as *firm generator* when it is able to meet the required generation target with 100% certainty.
- Technologies that can help reduce or even remove variability are *firm power enablers*, which usually are summarized into five kinds.
- Each firm power enabler, while being attractive in its own respect, has disadvantages. For example, batteries are at present costly.

[1] Perez M, Perez R, Rábago K R, et al. Overbuilding & curtailment: The cost-effective enablers of firm PV generation. Solar Energy, 2019, 180: 412-422. FIG. Firm PV Power Enablers



Geographic smoothing







Demand response

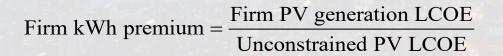


PV Overbuilding

FIRM PV POWER: OVERBUILDING AND STORAGE

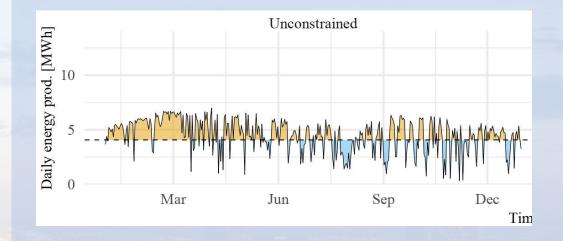
• **Overbuilding and Storage Example: 2x**

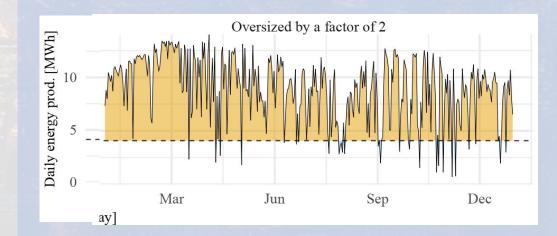
- For the non-oversized PV plant, much energy deficit is seen, which needs to be supplied through electric storage
- For the 2x overbuilt PV plant, the energy deficit is substantially reduced. Clearly, a combination of these enablers is attractive.
- We study firm power delivery through battery storage and PV overbuilding.
 - Metric: Firm kWh premium



LCOE: Levelized Cost of Energy

FIG. Firm PV Power With and Without Overbuilding





FIRM PV POWER: RESULTS

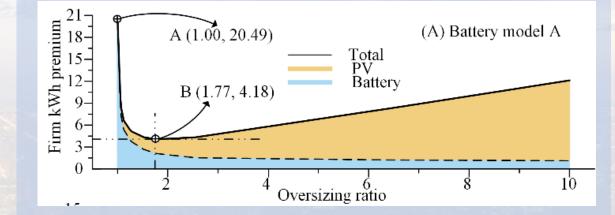
Firm kWh Premium Versus Oversizing

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When X_s = 1, i.e., no oversizing, a high firm kWh premium of 20 is obtained. However, with just a small fraction of overbuilding, there is a drastic decrease in the firm kWh premium---when X_s = 1.8, the firm kWh premium sees a five-fold reduction, reaching just 4.2. As more PV is overbuilt, the premium starts to increase quasi-linearly.

Par.	Value	Par.	Value
Cb	137 \$/kWh	Cs	833 \$/kW

FIG. Firm kWh premium versus oversizing ratio



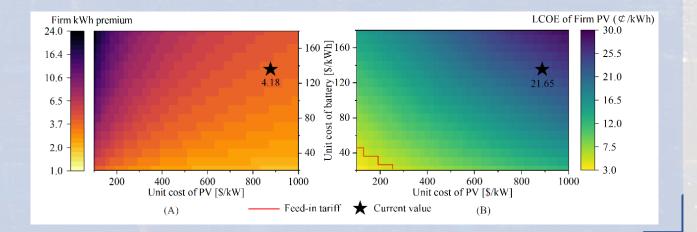
FIRM PV POWER: CONCLUSIONS

• **Firm PV Power Conclusions**

- The lowest firm kWh premium occurs when the PV cost is high and battery cost is low, with $c_s = 1000$ \$/kW and $c_b = 20$ \$/kWh, the premium is just 1.88.
- The lowest firm kWh premium under the present-day cost structure at the northern China location is around 4.18, which is still too high.
- To drop the LCOE of firm PV below grid parity, the unit investment costs of PV and battery need to be lower than 250 \$/kW and 40 \$/kWh, respectively.

FIG. Firm kWh premium sensitivity to PV and battery costs

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THANK YOU!