Evaluating Error Propagation Across the Photovoltaic Modeling Pipeline Through Blind Modeling

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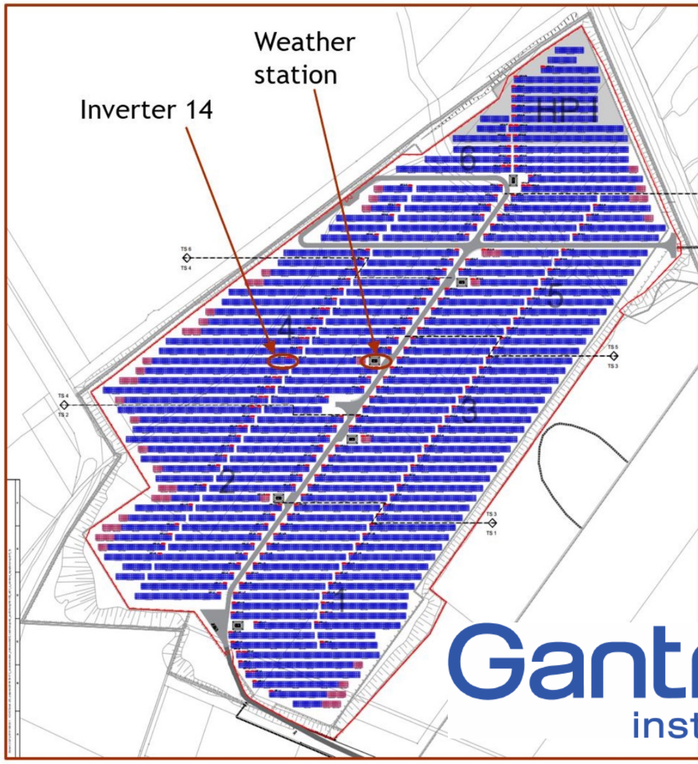
What is 'Blind Modeling'

- Knowing the 'answers' when modeling can inadvertently influence modeling choices.
- 'Blind' modeling is when the 'answers' are not considered.
- System/weather data provided then POA, Tmod, and power are modeled.
- Ensures there is no way for modeler bias (conscious or unconscious) to influence the results.

Motivations for This Study

- Other studies could not pin down at what step of the modeling pipeline specific errors were occurring, so it is unclear how much of the total error originates at different stages.
- Only small, lab-scale systems were studied in previous comparisons.
- This study was designed to occur in iterations to prevent accumulation of errors across the modeling steps and examine modeling practices.
- Gantner Instruments has provided real, operational system data which enables the use of realistic systems in the modeling exercise.

Two Systems in this Study



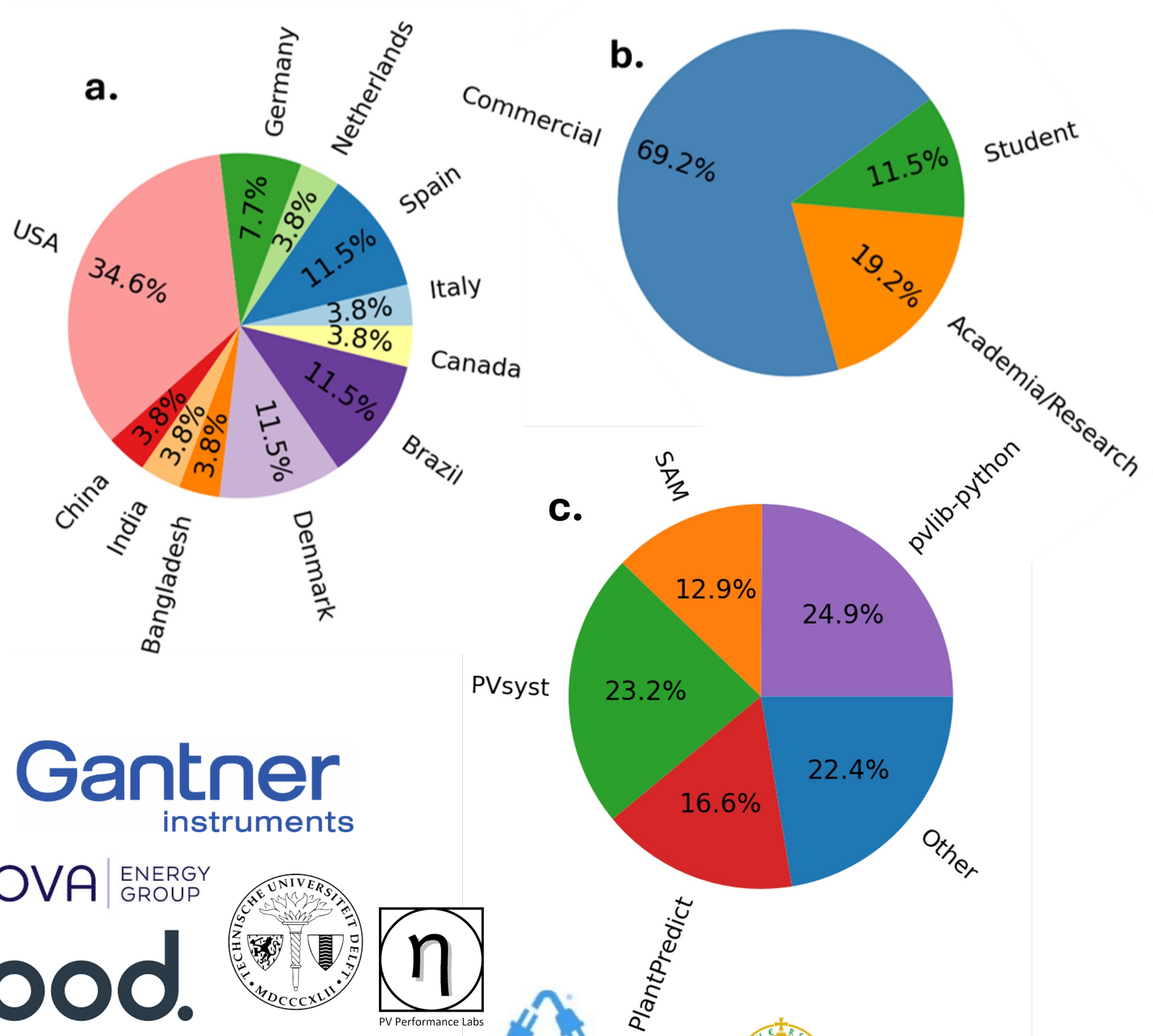
Gantner instruments

Germany, 14.5 MW
5-min and hourly
PAN file supplied later
Inverter and site-level
AC and DC

Albuquerque, NM, 15.4 kW
PAN file, IEC 61853-1 Matrix,
1-min and hourly
IAM + NMOT values
DC Only

Participant Statistics

- 31 Participants
- 11 Countries
- 5 total stages per participant, each at 2 participant, each at 2 timesteps totaling 252 data files submitted!!



Iterative Process

Stage 0*	Stage 1	Stage 2
Sandia provides GHI, DHI, DNI irradiance, other weather data, and system details.	Sandia provides measured POA irradiance, other weather data, and system details.	Sandia provides measured module temperature and derate guidelines.
Participants simulate POA irradiance, module temperature, and power.	Participants simulate model temperature and power using measured POA irradiance.	Participants use measured POA irradiance and module temperature to re-simulate power output with given derate guidelines.

*Albuquerque only

Iterative Process

Stage 0*

Sandia provides GHI, DHI, DNI irradiance, other weather data, and system

Participants simulate POA irradiance, module temperature, and power.

*Albuquerque only

Stage 1

Sandia provides measured POA irradiance, other

module temperature and power using measured POA irradiance.

Stage 2

Sandia provides measured module temperature and derate guidelines.

Participants use measured POA irradiance and module temperature to re-simulate power output with given derate guidelines.

Uncertainty around if changes were due to removal of derates or addition of measured temperature

Error Propagation – How do intermediate models contribute to energy error?

Stage 0 → Stage 1: Difference is attributable to POA errors
Stage 1 → Stage 2: Difference is attributable to Temperature modeling errors

Stage 2 results needed adjusting using the assumed derates/losses reported.

$$Total\ Fixed\ Derate = 1 - \prod_i (1 - L_i)$$

For example:

Soiling assumed to cause 1% loss, $L_{soiling}$ = 0.01
Wiring losses assumed to cause 2% loss, L_{wiring} = 0.02
Total Fixed Derate: 2.98%, Stage 2 power derated by this amount

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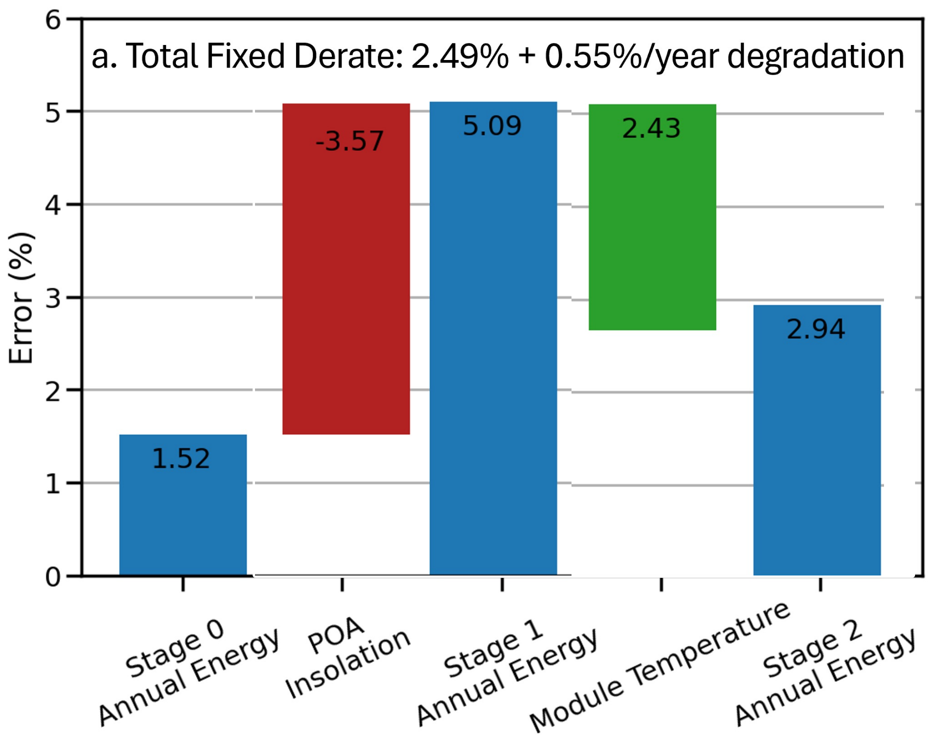
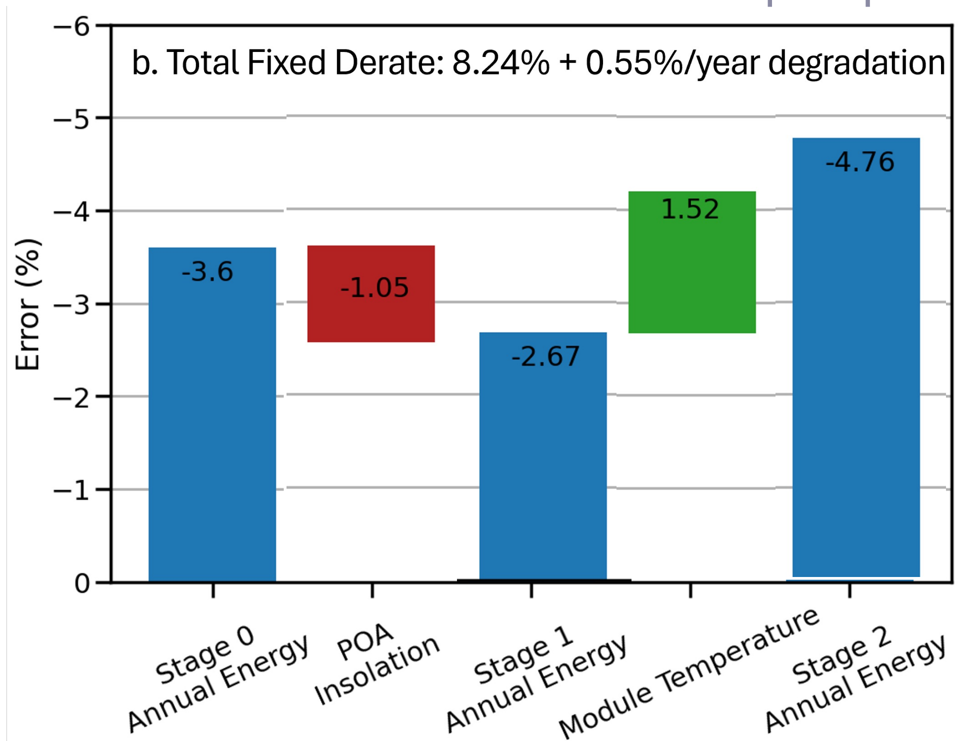
Error Propagation – How do intermediate models contribute to energy error?

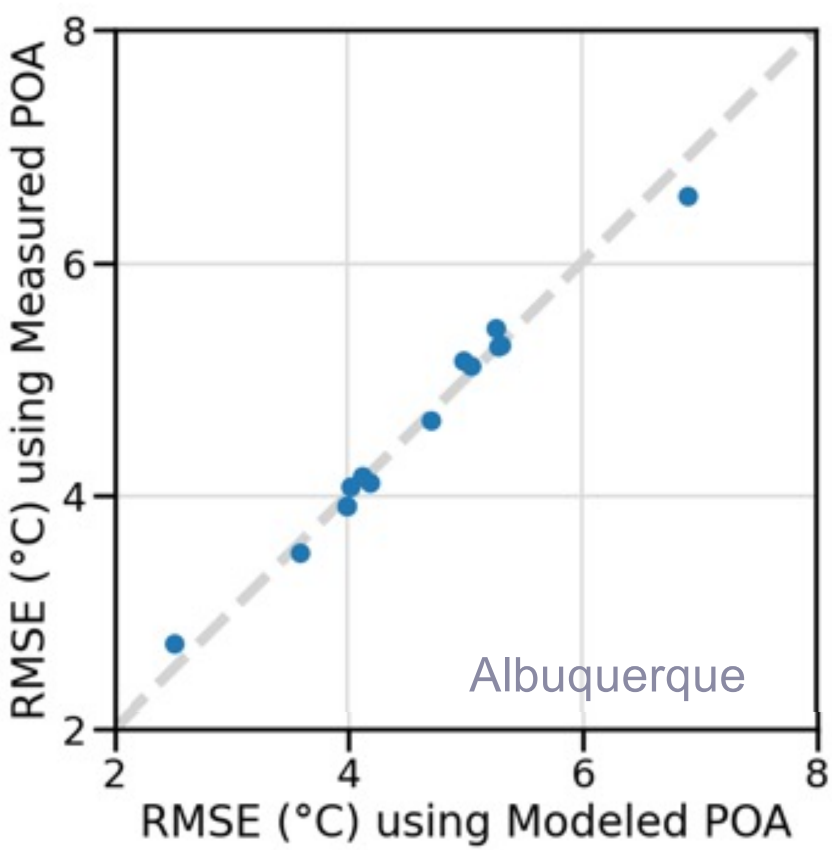
Albuquerque





Errors in POA irradiance and temperature modeling propagate directly into the performance model, with the resulting error magnitude being on the same order as the errors introduced in the POA or temperature estimation steps

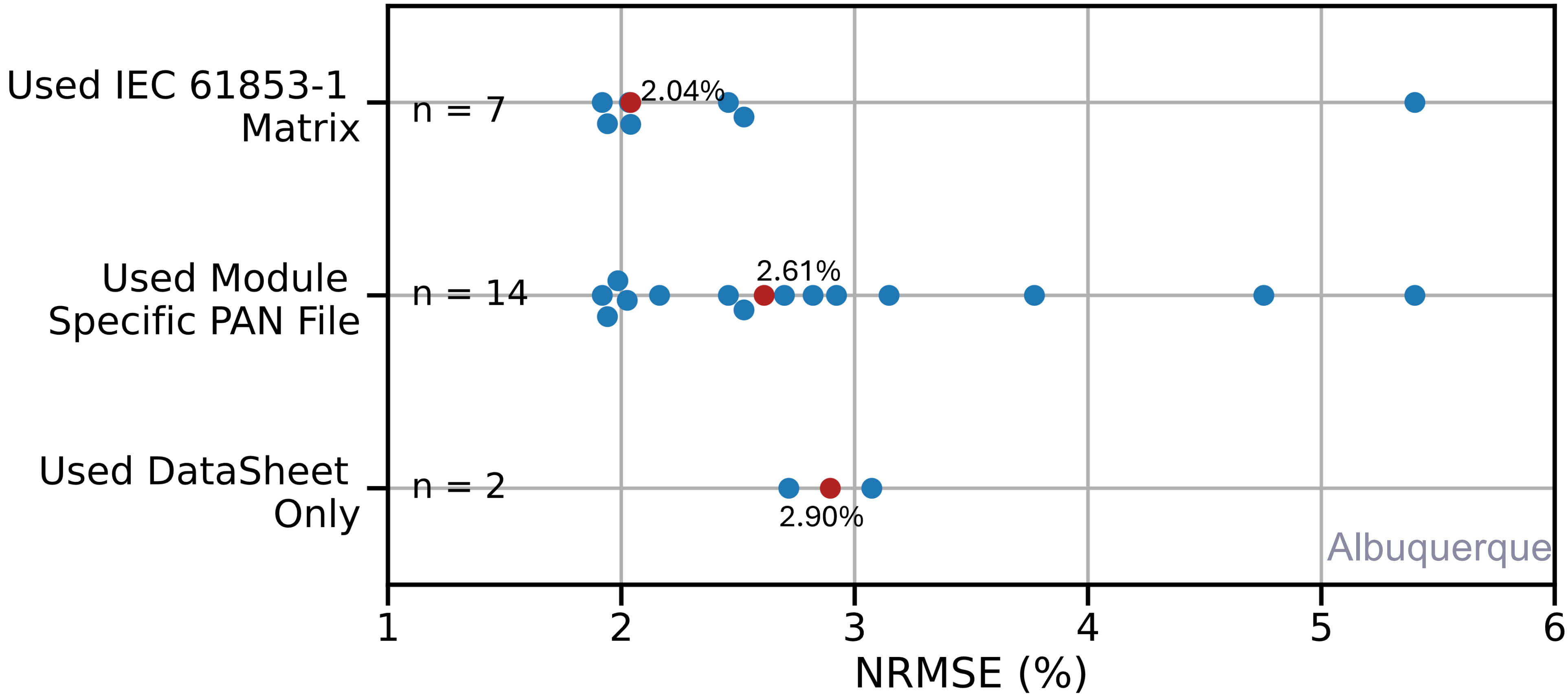
Error Propagation – How do intermediate models affect each other?



- We can compare the temperature model result when the participants' modeled POA was used vs when the measured POA was provided

Errors in the module temperature model showed very little change (<0.20 °C) when using measured versus modeled POA, indicating that errors in temperature model are more strongly influenced by low model sophistication or choice of model parameters.

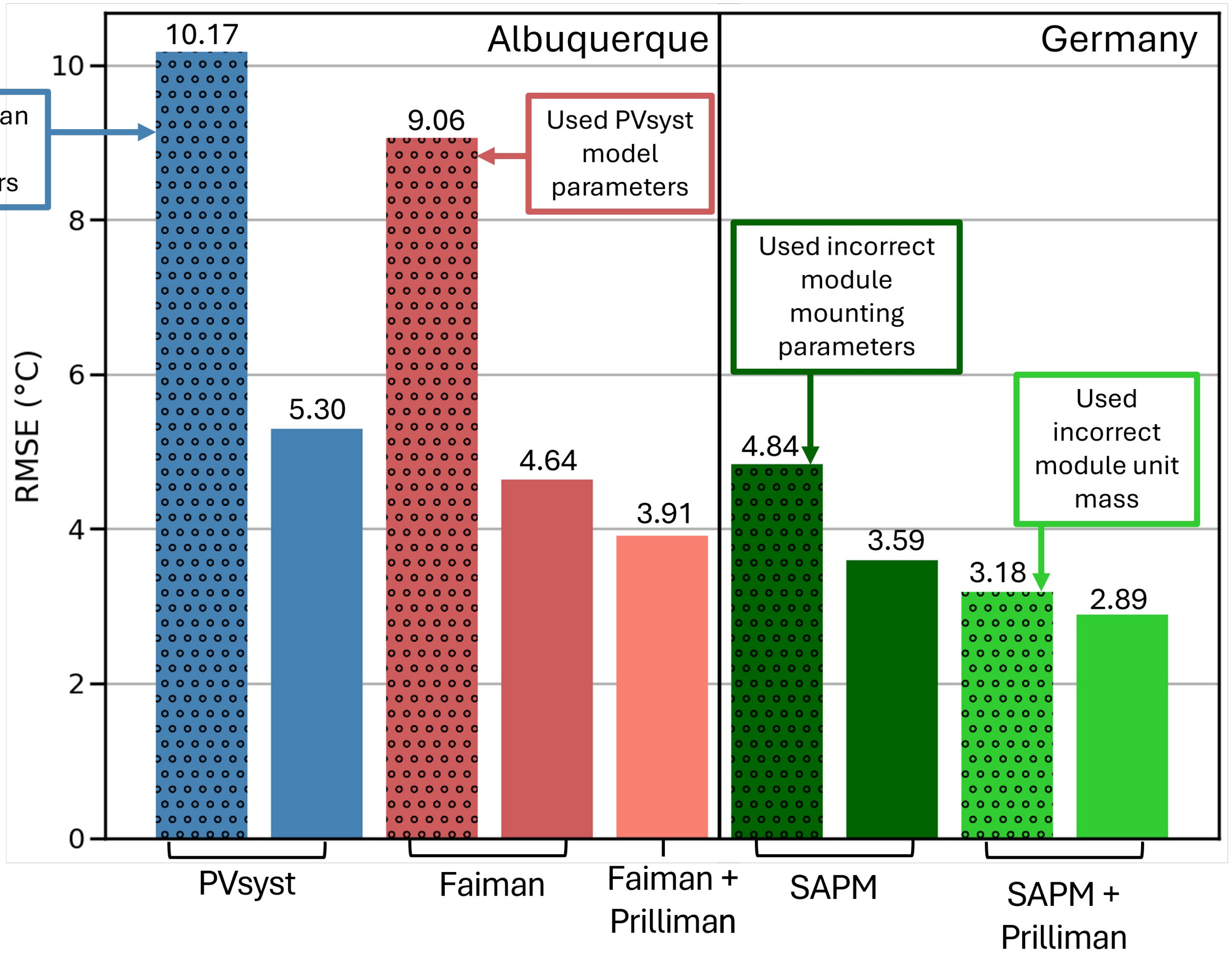
User Choices in Modeling – Data Source



Utilizing module-specific measurement data beyond standard datasheet values reduced modeling error, with IEC 61853 matrices providing the greatest improvement (**0.86%**), while PAN files showed smaller gains (**0.29%)** in both locations.

User Choices in Modeling – Temperature Parameters

Three primary module temperature models were used, but in each of these models there was confusion regarding the appropriate parameter values (Uc and Uv in PVsyst, U1 and U0 in Faiman, a and b in SAPM). This led to a **4.87 °C** difference in RMSE among participants using the same model, but erroneous parameters.



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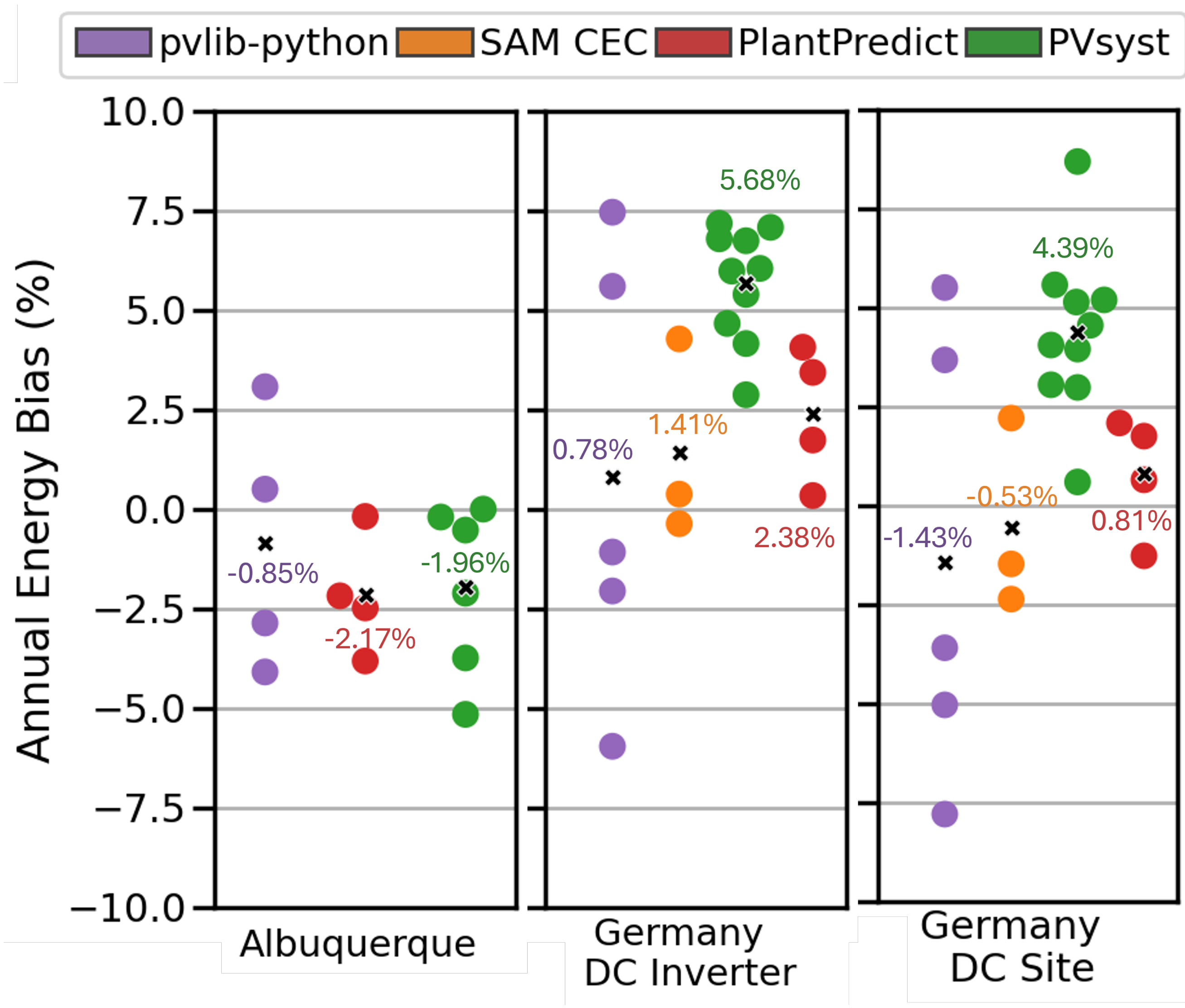
User Choices in Modeling – Modeling Software vs Library



Using a modeling software led to a smaller spread of bias error across participants (as low as **3.56%** in the lab-scale system) over the pvlib - python based implementation of PVWatts, which showed error spreads up to **7.24%** in the lab-scale system and **13.40%** in the utility-scale system.

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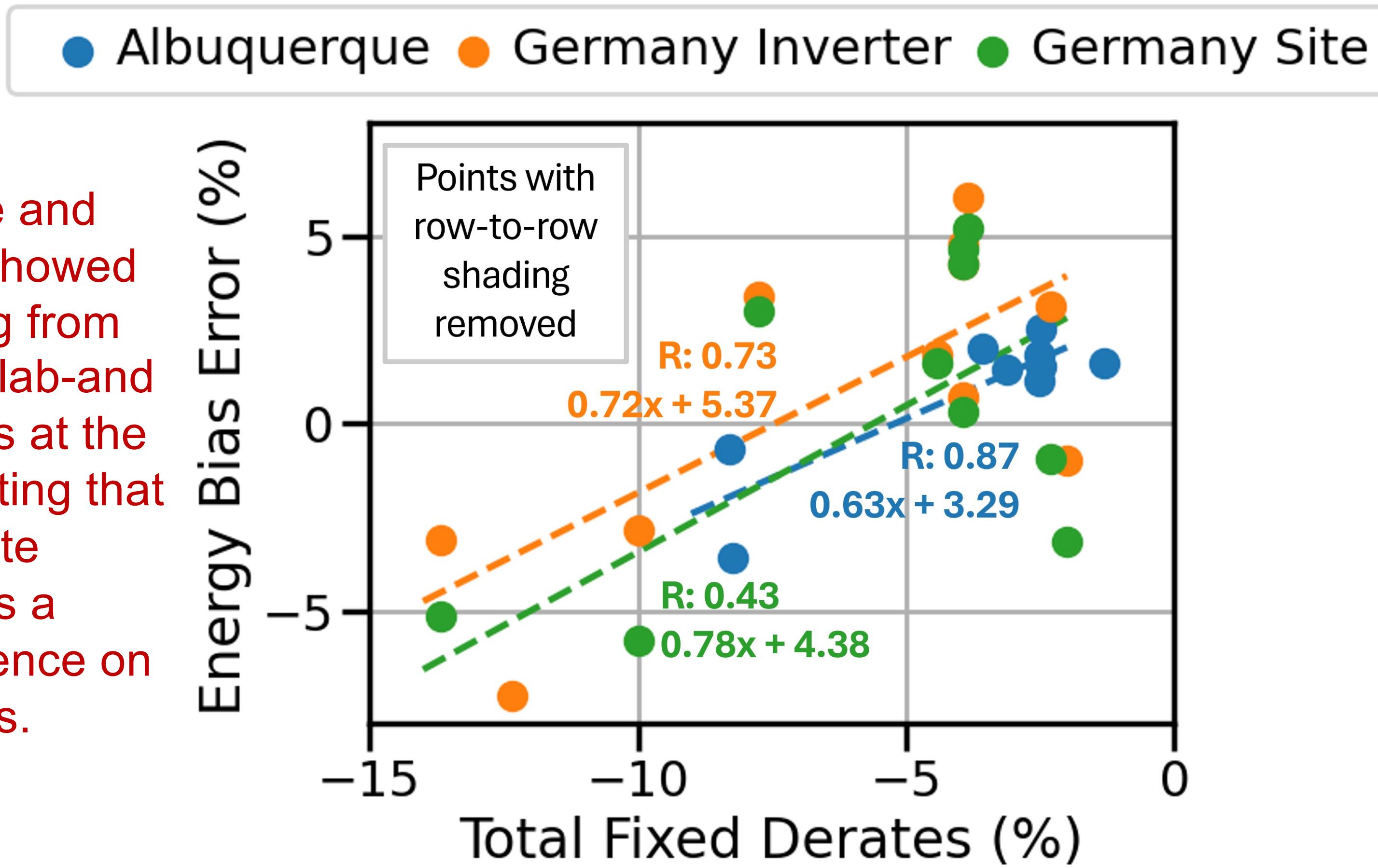
User Choices in Modeling – Derate Assumptions

Total fixed derate and energy bias error showed correlation ranging from 0.87 to 0.73 for the lab-and utility-scale systems at the inverter level, indicating that choice of derate assumption has a non-negligible influence on the model bias.



Recommended Best Practices

- Account for POA and temperature modeling errors within overall energy error ‘budget’ and report their uncertainties.
- Focus efforts to improve temperature model outputs on selecting appropriate parameters rather than refining POA.
- Incorporate module-specific data beyond datasheet values when available, use open-source methods to translate.
- Implement checks for temperature model parameters and use open-source translation methods.
- Select modeling workflow based on your … of reproducibility and flexibility.
- Leverage measured data from operat… nform derate assumptions & consider probabil… modeling.

TABLE III

LESSONS LEARNED FROM THE BLIND MODELING COMPARISON AND CORRESPONDING BEST PRACTICES FOR IMPROVING PV PERFORMANCE MODELING WORKFLOWS.

Finding from this study	Recommended Best Practice to Implement Moving Forward	Supporting Figure
Errors in POA irradiance and temperature modeling propagate directly into the performance model, with the resulting error magnitude being on the same order as the errors introduced in the POA or temperature estimation steps	Account for POA and temperature modeling errors within the overall energy error 'budget' and report the associated POA and temperature modeling uncertainties when reporting energy estimations.	Fig. 5
Errors in the module temperature model showed very little change (<0.20 °C) when using measured versus modeled POA, indicating that errors in temperature model are more strongly influenced by low model sophistication and choice of model parameters.	Focus efforts to improve module temperature model outputs on selecting appropriate parameters, rather that refining POA inputs solely to improve temperature model accuracy.	Fig. 6
The mean and spread of NRMSE values at each stage were more than 2x in utility-scale system than the lab-scale system.	Avoid applying assumptions validated at one system scale universally across all sizes. Account for increased uncertainty in larger systems due to spatial variations in irradiance and temperature, increased electrical mismatch, etc.	Fig. 7

Full table covering all topics is featured in our upcoming article. Under revision by co-authors and will be submitted soon after.

Who is


PVPerformance
MODELING COLLABORATIVE
~~AMERICA'S~~ NEXT
top PV modeler ?

All of us!

Blind Modeling – Software Comparison

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Feature review of photovoltaic modeling software utilizing blind performance assessment

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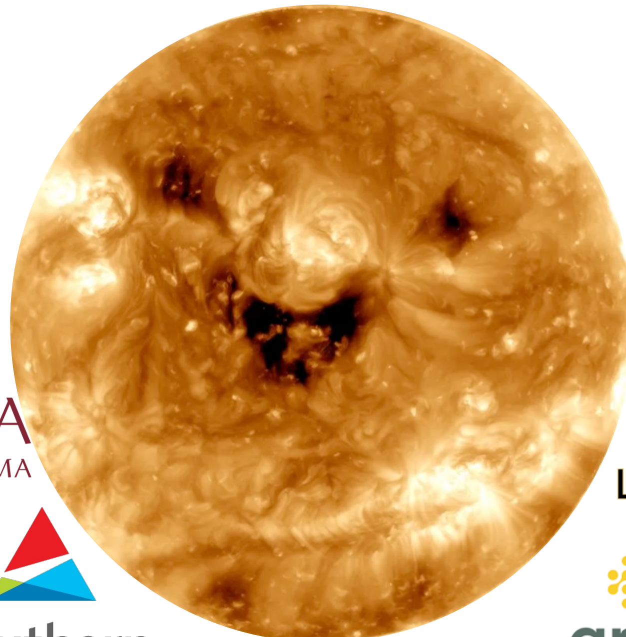
THANK YOU!



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SOL-PHI ENGINEERING

STANDARD SOLAR

LEEWARD renewable energy

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Thank you for attending today's presentation.