Classification Method to Predict the Effect of Short-Term Inverter Saturation on PV Performance Modeling

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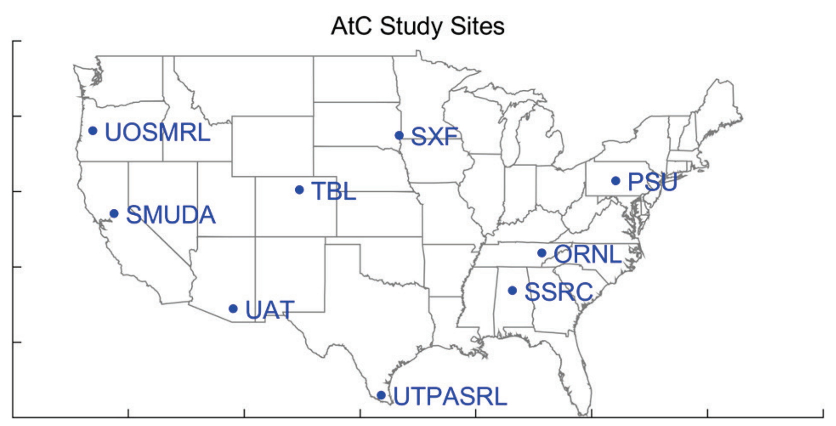
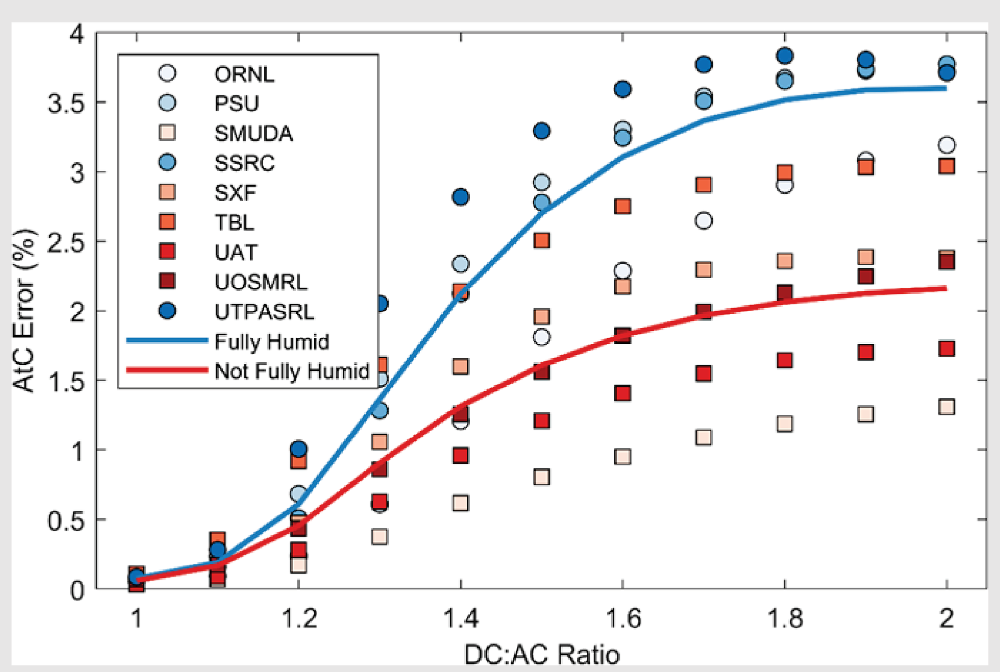
Introduction

Hourly PV models overestimate output by 0.5 – 4% due to the Average-then-Clip (AtC) bias.

PV projects are generally planned using hour-averaged data from typical meteorological years to predict power and energy output. However, inverters clip power instantaneously and calculations that clip hour-averaged data will overestimate ac power output during hours in which intermittent clipping occurs. We have quantified this error, the “Average-then-Clip (AtC) bias”, using measured dc power (P_{dc}) and modeled inverter performance; the measurements were minute data from a test site in Birmingham, AL, which had oversized inverters and no clipping.

We then modeled the AtC bias at 9 locations using 1-minute radiation and meteorological data. These models included PV module thermal mass which we have shown is needed for accurate AtC bias modeling. The AtC bias was significant and variable, causing up to 4% overestimation of predicted energy for modeled single-axis tracking installations in humid subtropical locations with a dc:ac ratio of 2.0. AtC biases were positively correlated with dc:ac ratios and insolation variability and show dependence on whether a site is “fully humid” or not as defined by the Köppen climate classification.





AtC bias for the 1Axis installation at nine sites grouped by Koppen “Fully Humid” and “Not Fully Humid” climates. Fully Humid sites are shown as blue circles; Not Fully Humid sites as red squares.

Objective and Data

Estimate AtC bias generally using classification of 3.5 million hours of “observation” from 9 sites and 2 installation types.

Objective

Using the data, models and insights from our phenomenological exploration of the AtC bias (see references), we classified hourly data based on clearness indices and clipping potential. This method is designed to estimate average AtC bias for a range of locations, installation types, and dc:ac ratios.

Classification Data

- 9 sites, each with 1-7 years of data
- 2 Installations (South-facing 25 tilt, Single axis)
- 11 dc:ac ratios from 1.0 – 2.0
- 324,000 hours of data
- 3.5E6 hourly “observations”

Calculations

Minute-scale PV output data were used to calculate AtC bias. Hourly AC power output was calculated as

$$\overline{P}_{ac,CtA} = \frac{1}{n}\sum_{i=1}^{n} f(P_{dc,i}, V_{dc,i})$$

where

n - number of minutes in hour

f - inverter model

$P_{dc,i}$ - minute dc power

$V_{dc,i}$ - minute dc voltage

Average then Clip AC power output was calculated as

$$\overline{P}_{ac,AtC} = f(\overline{P}_{dc}, \overline{V}_{dc})$$

where

$\overline{P}_{dc}$ - hour average dc power

$\overline{V}_{dc}$ - hour average dc voltage

The error relative to nominal annual output was

$$\delta = \frac{\overline{P}_{ac,AtC} - \overline{P}_{ac,CtA}}{\sum \overline{P}_{ac,CtA}} \times 100$$

Note that δ is a ratio of hourly error to annual production, and so is generally less than 1E-4.

Classification variables include radiation scaled by dry clean sky conditions

$$\gamma_{DNI} = \frac{DNI}{DNI_{DryClean}} \qquad \gamma_{GHI} = \frac{GHI}{GHI_{DryClean}}$$

and clipping potential

$$CP = \frac{P_{dc,DryClean} - P_{ac,0}}{P_{ac,0}}$$

where

$P_{dc,DryClean}$ - dc power under dry clean sky

$P_{ac,0}$ - inverter ac power capacity

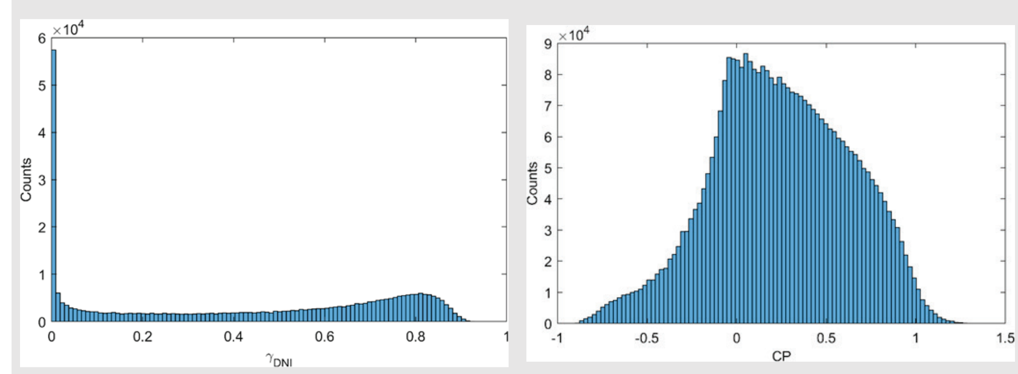
Method

Classify hours by radiation index and clipping potential, then average AtC bias for each subset of hours.

Selected 20 bins manually for each of the possible classification variables, γ_{DNI}, γ_{GHI}, RH, and CP.

For each of 16 combinations of 0 to 3 classification variables

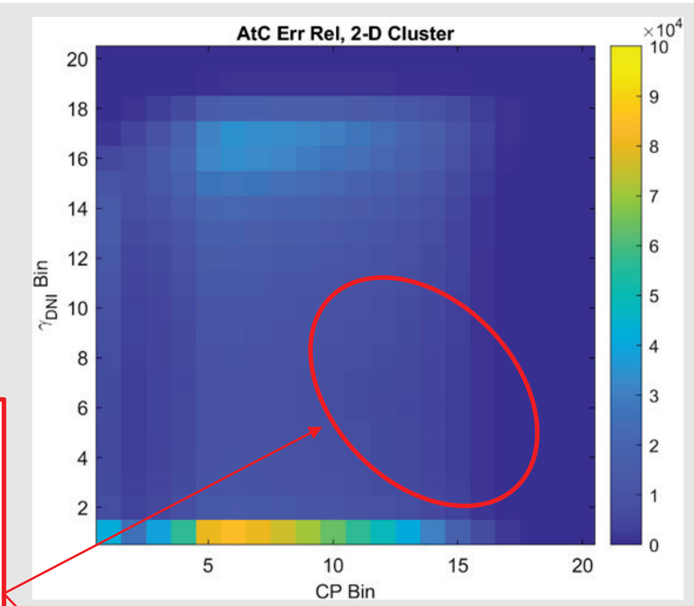
- For each of 9 sites
  - Generate averaged AtC Bias matrix using the other 8 sites
  - Apply average AtC Bias from matrix for each matching hour
  - Compare measured vs estimated AtC Bias
- Collect mean squared error for all sites



DNI index was bimodally distributed with a mode near zero. Clipping Potential had a unimodal distribution with peak near zero.

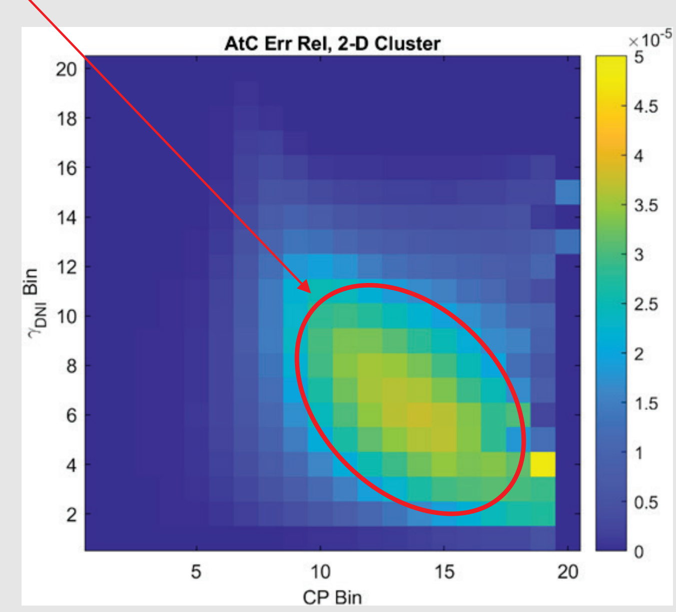
The classification method based on γ_{DNI} and CP performed best. The addition of RH made little improvement to the method. GHI data may be used when DNI data are not available.

Counts of hourly observations classified by DNI Index and Clipping Potential.



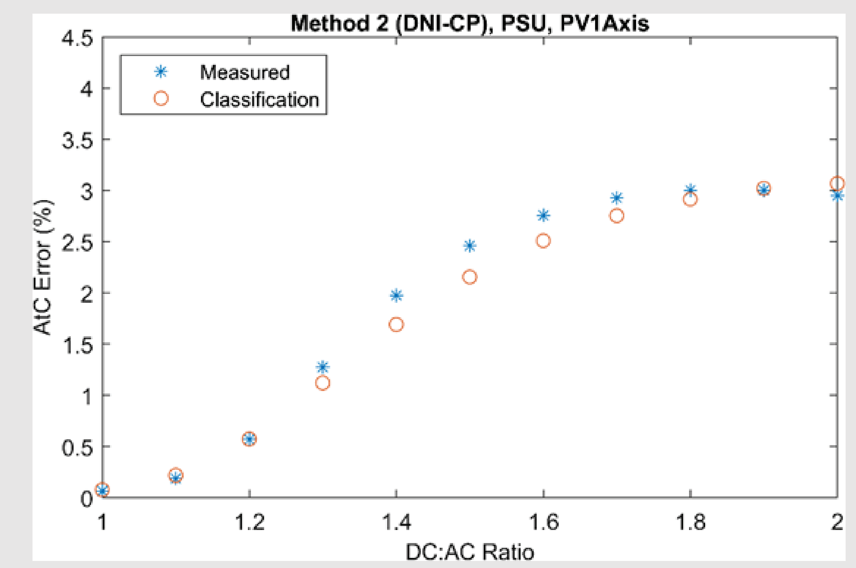
Relatively few observations contribute to AtC Bias, and these can be distinguished by moderate DNI Index and high Clipping Potential.

Average Scaled AtC Bias, δ, classified by DNI Index and Clipping Potential.

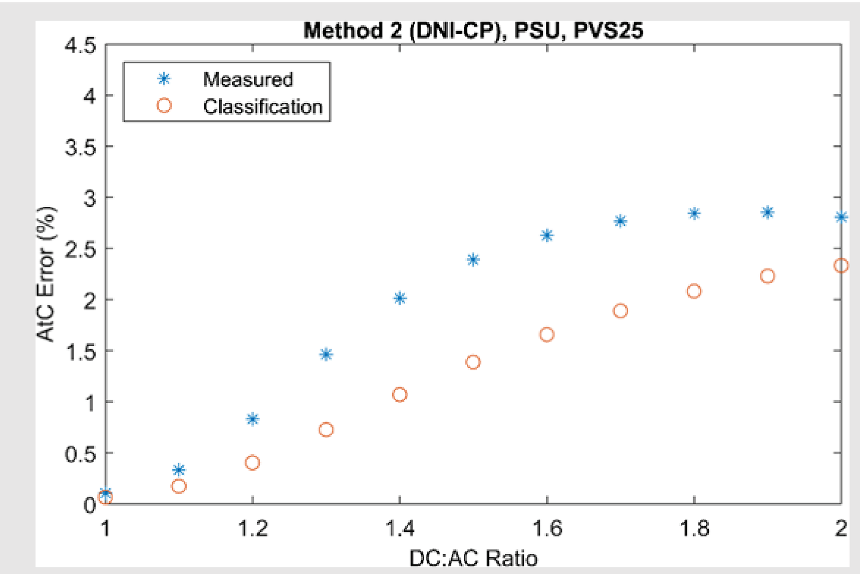


Results

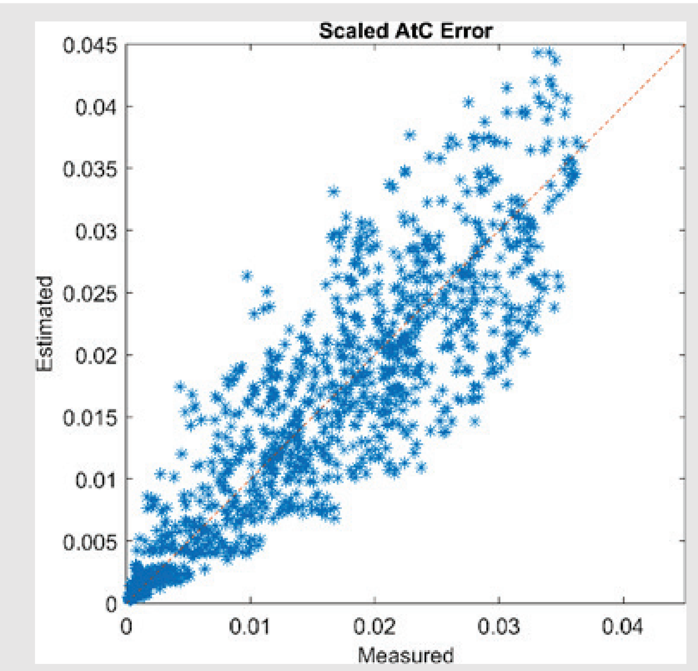
Estimated annual AtC biases reproduce main features of “measured” values, are unbiased, and match within ~50%.



Measured and estimated AtC error averaged over 8 years for the 1Axis installation at PSU as a function of dc:ac ratio.



Measured and estimated AtC error averaged over 8 years for the S25 installation at PSU as a function of dc:ac ratio.



Comparison of measured and estimated annual AtC bias for the 1166 cases in the data set.

Solution

This method can be used by the PV modeling community to estimate AtC bias generally and accurately.

1. Calculate annual P_{ac} output for the site using TMY hourly input data and dc:ac ratio of 1.0. This is the nominal annual PV output.
2. Calculate hourly clean dry sky radiation components using a solar model.
3. Calculate hourly clean dry sky P_{dc} using clean dry sky radiation, TMY meteorology, and a PV model.
4. Calculate DNI radiation index, γ_{DNI}, for each hour.
5. Calculate clipping potential, CP, for each hour.
6. For each hour, lookup average AtC bias from 20×20 matrix based on γ_{DNI} and CP.
7. Sum hourly average AtC bias over the year.
8. Multiply this sum by the nominal annual P_{ac} output; subtract this from the annual P_{ac} output calculated using hour-scale models to correct for the AtC bias.

The average AtC bias matrices are available from the authors as a CSV file. The procedure will generate characteristic AtC bias for each hour; these may be summed to yield estimates of the AtC bias. The accuracy of these estimates for annual AtC bias are within ±1% of annual PV output; the accuracy for shorter averages, e.g., month-hour averages, is unknown and these should be used with caution.

AtC bias may also be estimated using GHI index if DNI data are not available. This method may be used to estimate AtC bias for specific installation types with improved accuracy but a loss of generality. Matrices of average AtC bias are also available from the authors for GHI index, single axis trackers, and fixed 25° south-facing installations.

Conclusion

We have developed and tested a classification method to correct for the AtC bias based on radiation index and clipping potential. The classification results generally reproduced the effect of dc:ac ratio, location, and installation on AtC bias. The AtC bias estimates were themselves unbiased and matched the measured values within 50% for single year comparisons.

This method may be used to estimate AtC error from hourly data, either as part of PV performance model software (e.g., tools like the System Advisor Model or PVsyst), or to correct the output outside of the model.

References

The Effect of Short-Term Inverter Saturation on PV Performance Modeling, J. O. Allen, W. B. Hobbs, and M. Bolen, PVPMC Meeting, 2019.

Predicting the Effect of Short-Term Inverter Saturation on PV Performance Modeling, J. O. Allen, W. B. Hobbs, and M. Bolen, PVPMC Meeting, 2019.

Acknowledgements

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