Data processing and quality verification for improved photovoltaic performance

PV Performance Assessment

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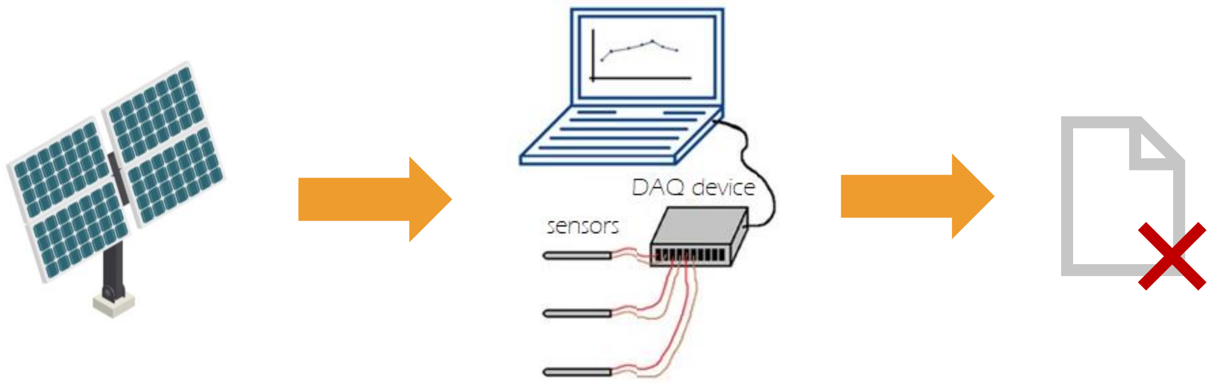
Why data quality matters

- Ensuring high-quality of data is crucial for the performance and reliability analytics of photovoltaic (PV) systems
- Field measurements commonly exhibit gaps, missing data and erroneous values caused by outages and component failures
- The processes applied to handle the acquired measurements can potentially introduce noticeable bias that obscures underlying PV performance analysis

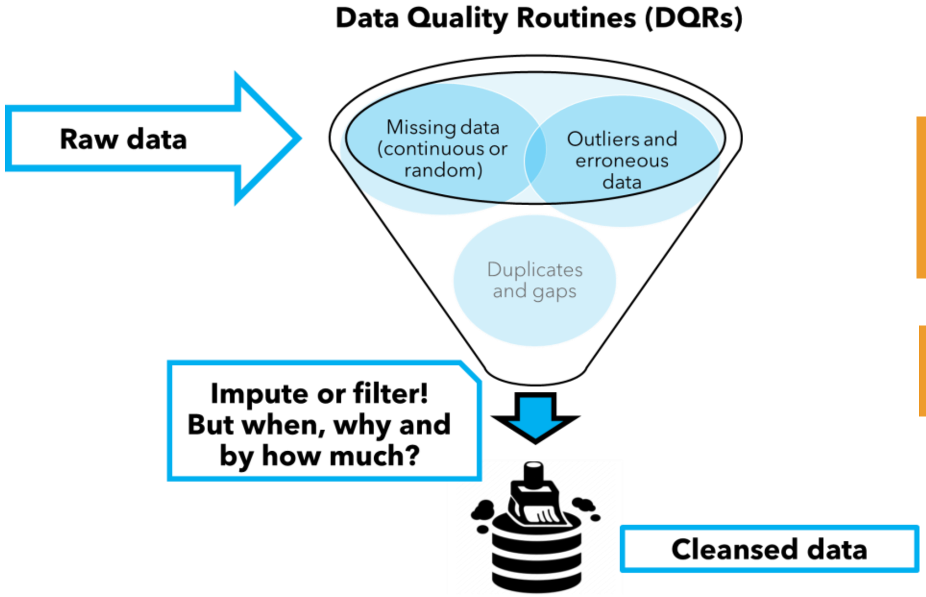


Background & Objective

- Existing standards (i.e. IEC 61724) and reports lack of specifications for handling invalid data (i.e. gaps, missing and erroneous values)

Specific Objective:

- To develop a complete and quantitative methodology of Data Quality Routines (DQRs) for data processing and quality checks



Provide a specific approach for handling invalid values and reconstructing PV datasets

Enable reproducible results in PV performance

Proposed DQRs

- Builds on IEC 61724 and other reports
- Comprises of 8 sequentially structured routines
- Main contribution on Step 6

Methodology - Approach

1. Experimental setup

- Test PV modules and systems in Arizona and Cyprus

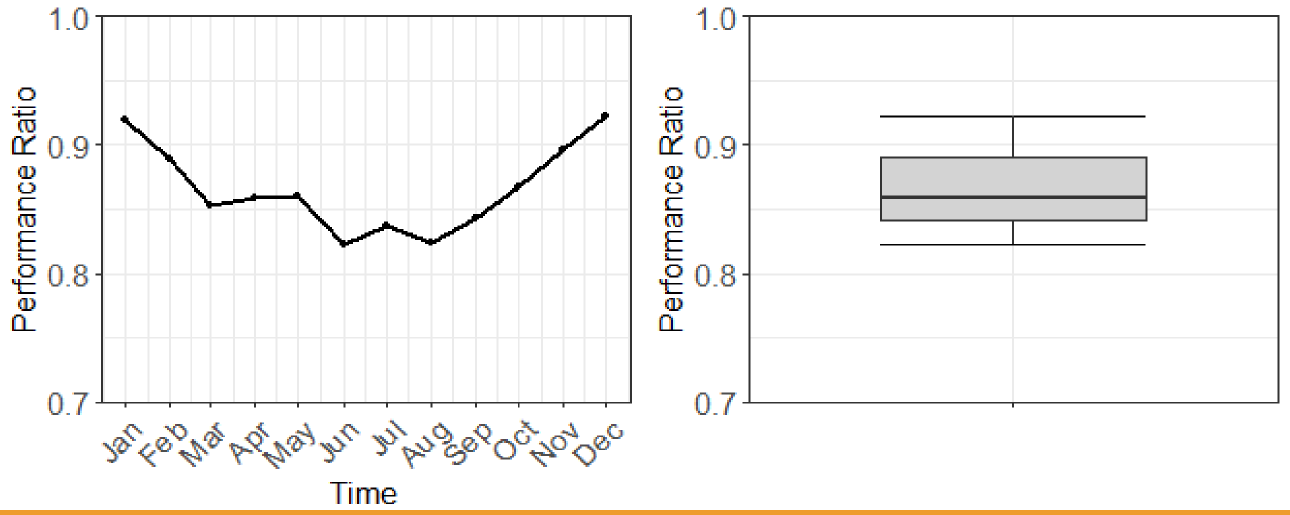
2. Data acquisition (DAQ) system

- Recording of electrical and meteo data
- Monthly DC Performance Ratio (PR) - Standard KPI in contractual agreements

3. Reference PV datasets

- 1-year and 5-year datasets (from a well-maintained PV module and system)

1-year reference PV dataset



Methodology - Approach

1. Experimental setup

- Test PV modules and systems in Arizona and Cyprus

2. Data acquisition (DAQ) system

- Recording of electrical and meteo data
- Monthly DC Performance Ratio (PR) - Standard KPI in contractual agreements

3. Reference PV datasets

- 1-year and 5-year datasets (from a well-maintained PV system)

4. Artificial invalid datasets

- Emulation of missing data into the reference dataset from 1% to 40% invalid data rate
- Process repeated 50 times for each invalid data rate (resulting in 2000 invalid datasets)

Methodology - Approach

5. Test cases
- Different test cases reflecting real PV monitoring scenarios of data loss

6. Invalid datasets reconstruction
- Invalid values treated by data deletion and inference techniques

7. Performance evaluation
- Comparison between reference and reconstructed datasets (PR and PLR metrics)
- Absolute percentage error (APE)

$$APE = \left|\frac{A_t - P_t}{A_t}\right|$$

where
A_t is the average monthly PR (or PLR) of the reference dataset
P_t is the average monthly PR (or PLR) of the 2000 invalid datasets

Methodology - 5. Test cases

- 6 different test cases were investigated reflecting real PV monitoring scenarios of data loss

Test Case	Missing measurements	Performance metric	Sequence of missing measurements
1	P_A	PR	Random
2	P_A	PR	Continuous
3	G_I	PR	Random
4	G_I	PR	Continuous
5	T_{mod}	PR_{TC}	Random
6	T_{mod}	PR_{TC}	Continuous

P_A is the array DC power
G_I is the in-plane irradiance
T_{mod} is the module temperature

Time	Variable X
t1	NA
t2	NA
t3	NA
t4	NA
…	…
tn	NA

Time	Variable X
t1	x1
t2	NA
t3	x3
t4	NA
…	…
tn	NA

Methodology - 6. Dataset reconstruction

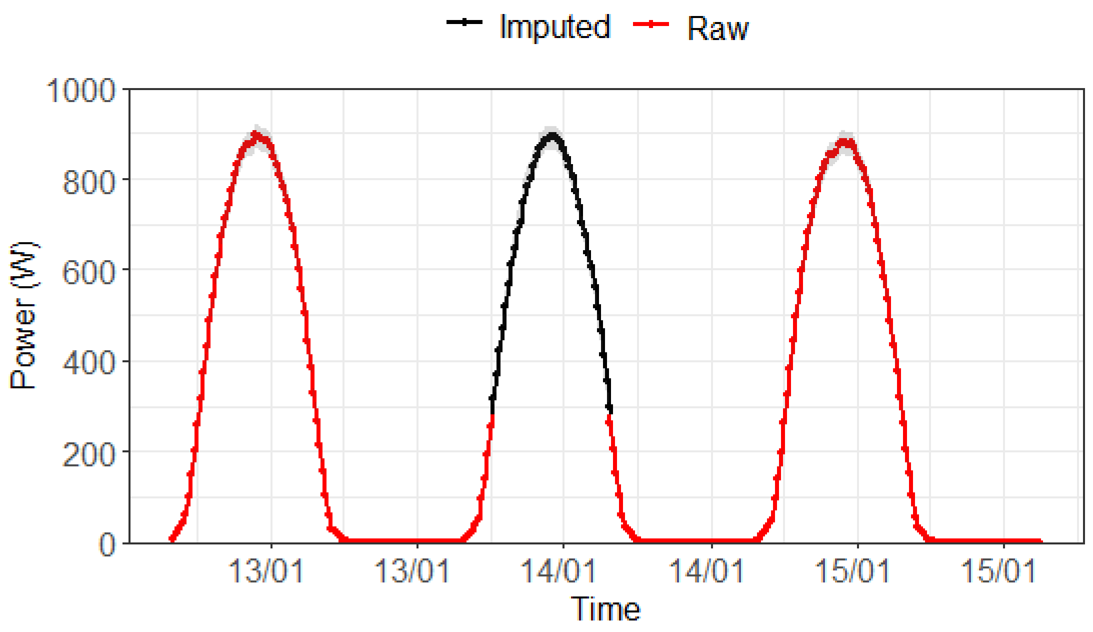
- Data deletion methods
  - “Row” deletion → all rows with at least one missing data point are deleted
  - “Value” deletion → only the missing values are removed

Timestamp	Variable X	Variable Y
t1	x1	y1
~~t2~~	~~NA~~	~~y2~~
t3	x3	~~NA~~
…	…	…
tn	xn	yn

Row deletion (row t2)
Value deletion (NA in row t3)

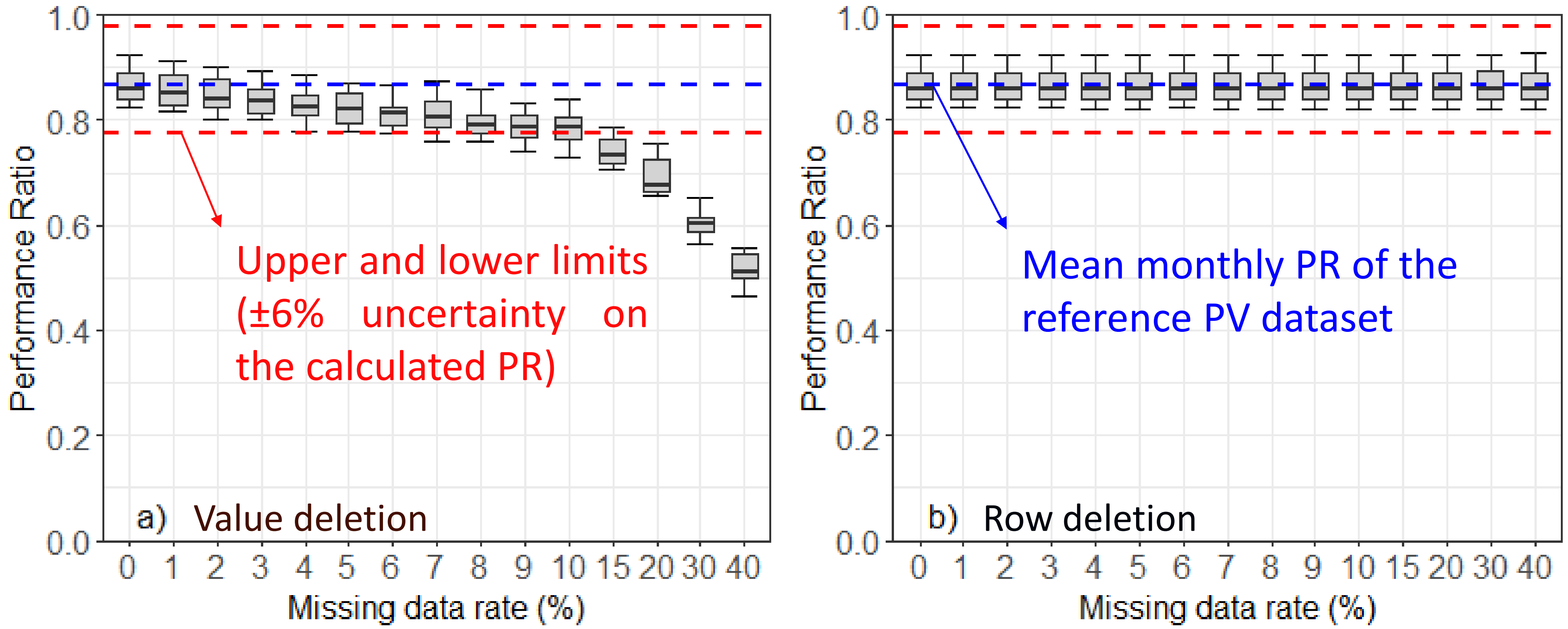
Methodology - 6. Dataset reconstruction

- Data inference methods (i.e. back-fill or impute missing data points)
  - Electrical models: Sandia Array Performance Model (SAPM), Sandia module temperature model (SMTM)
  - Multiple imputation: Predictive Mean Matching (PMM)
  - Univariate imputation: Random Forest (RF), bootstrap



Results - Data deletion methods

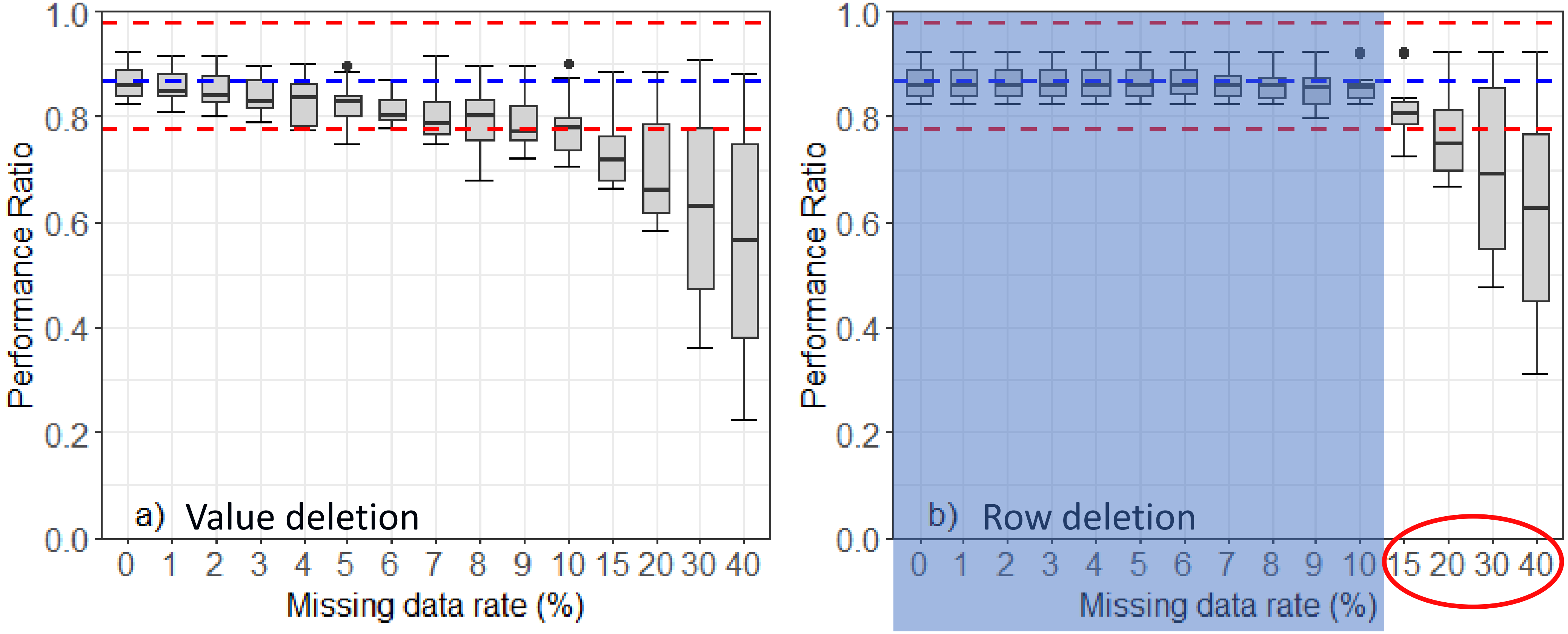
- 1-year PV datasets with random missing power measurements



The effect of random missing power measurements was mitigated by **row deletion**

Results - Data deletion methods

- 1-year PV datasets with continuous missing power measurements



Row deletion was effective for handling continuous missing power measurements up to 10%

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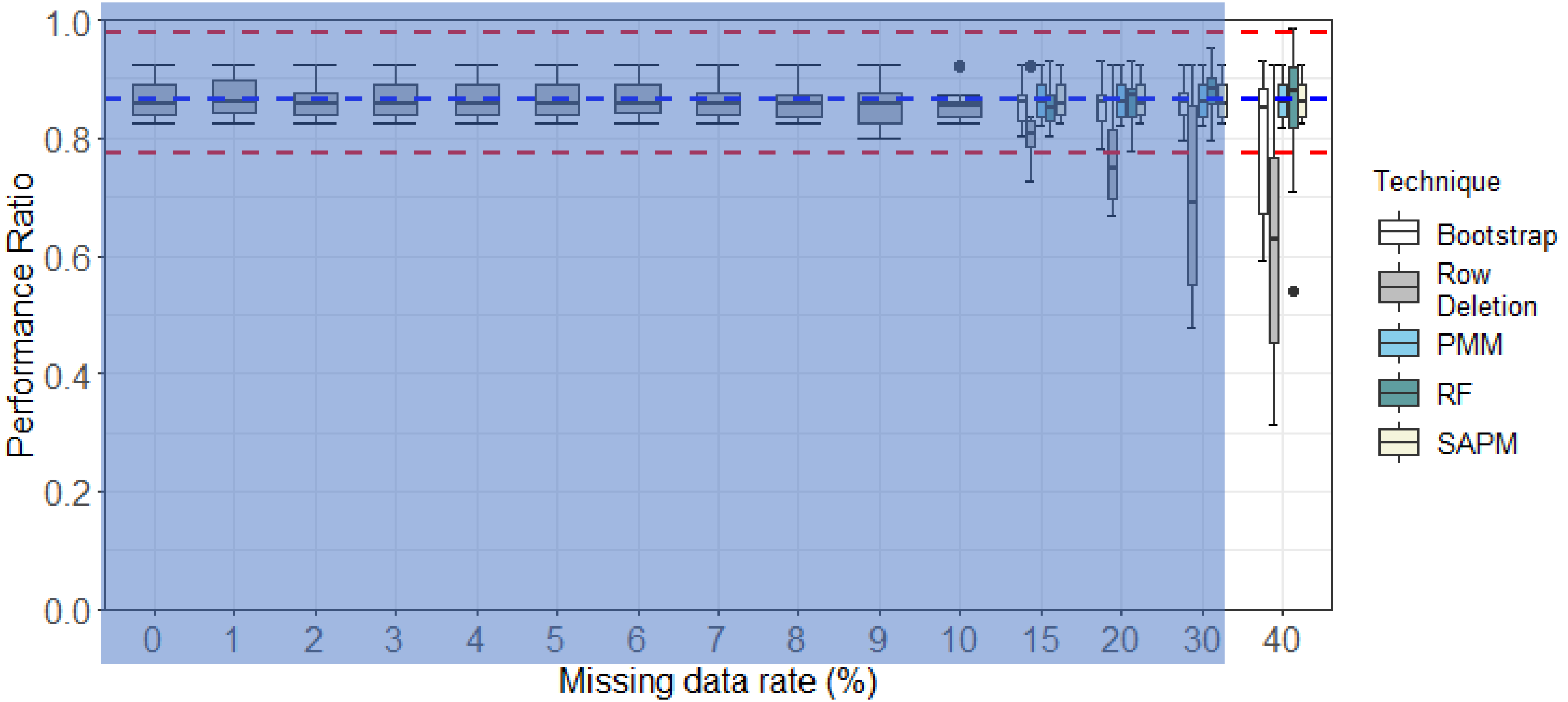
Results - Data inference techniques

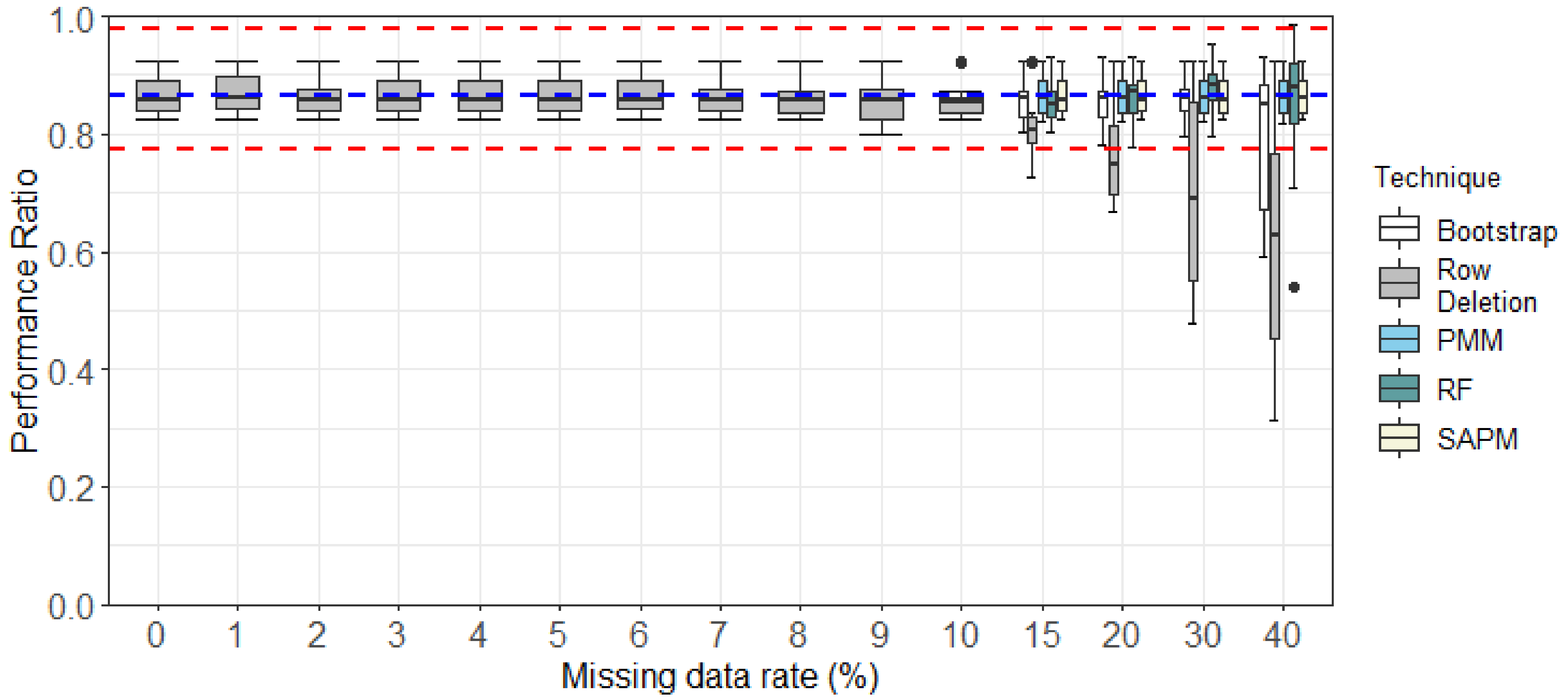
- Invalid missing power datasets were reconstructed by data inference techniques



Univariate imputation can be used for up to 30% missing data rate

Results - Data inference techniques

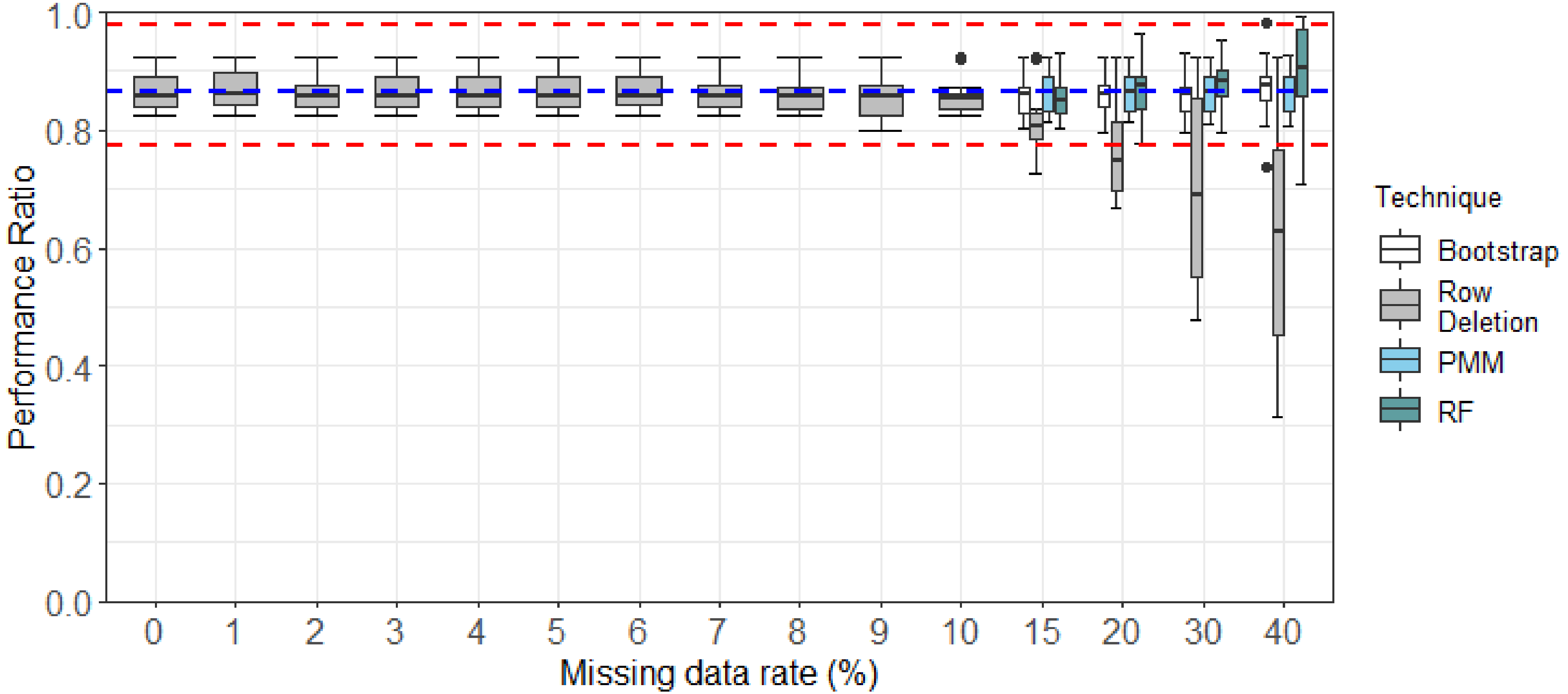
- Invalid missing power datasets were reconstructed by data inference techniques



Data inference with SAPM yielded the lowest error (max APE of 0.81%)

Results - Data inference techniques

- Invalid missing irradiance datasets were reconstructed by data inference techniques



Data inference with PMM yielded the lowest error (max APE of 1.97%)

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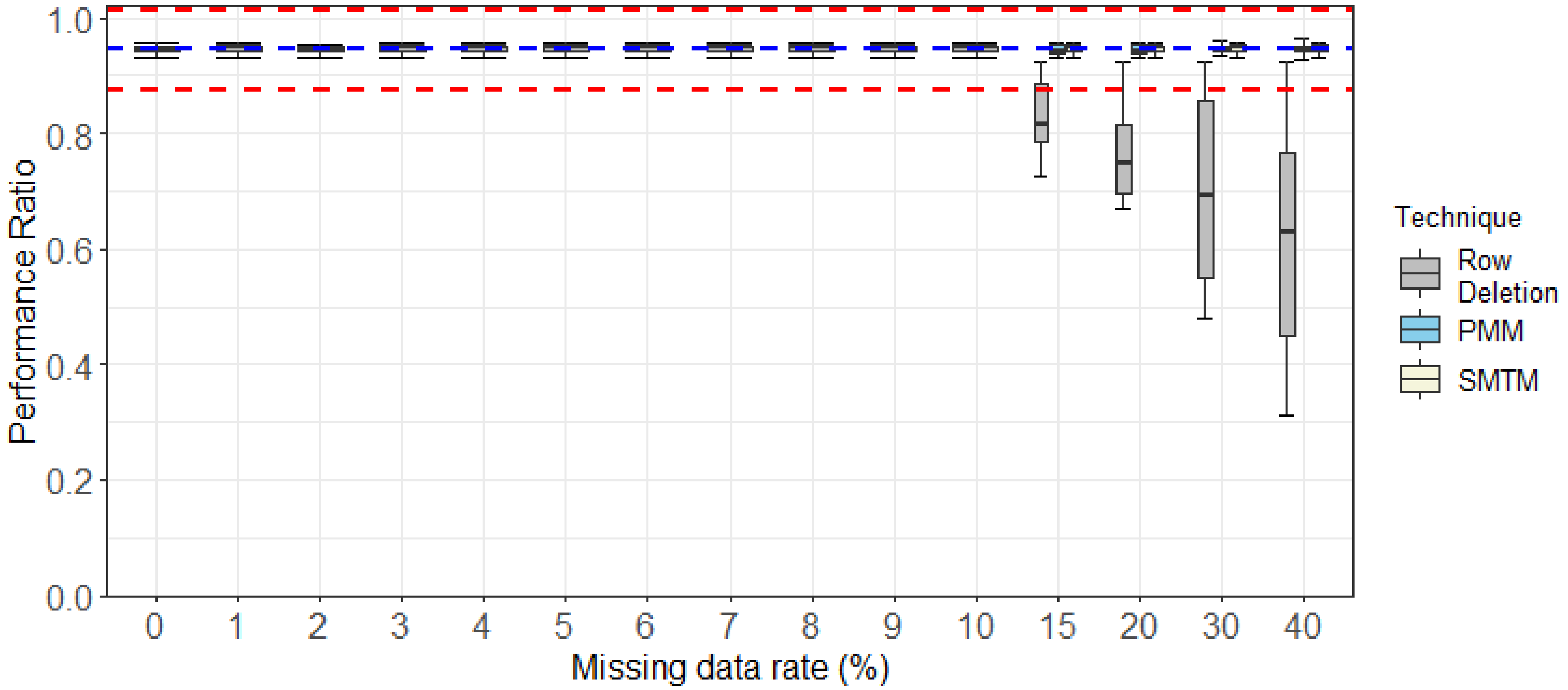
Results - Data inference techniques

- Invalid missing temperature datasets were reconstructed by data inference techniques



Data inference with SMTM yielded the lowest error (max APE of 0.28%)

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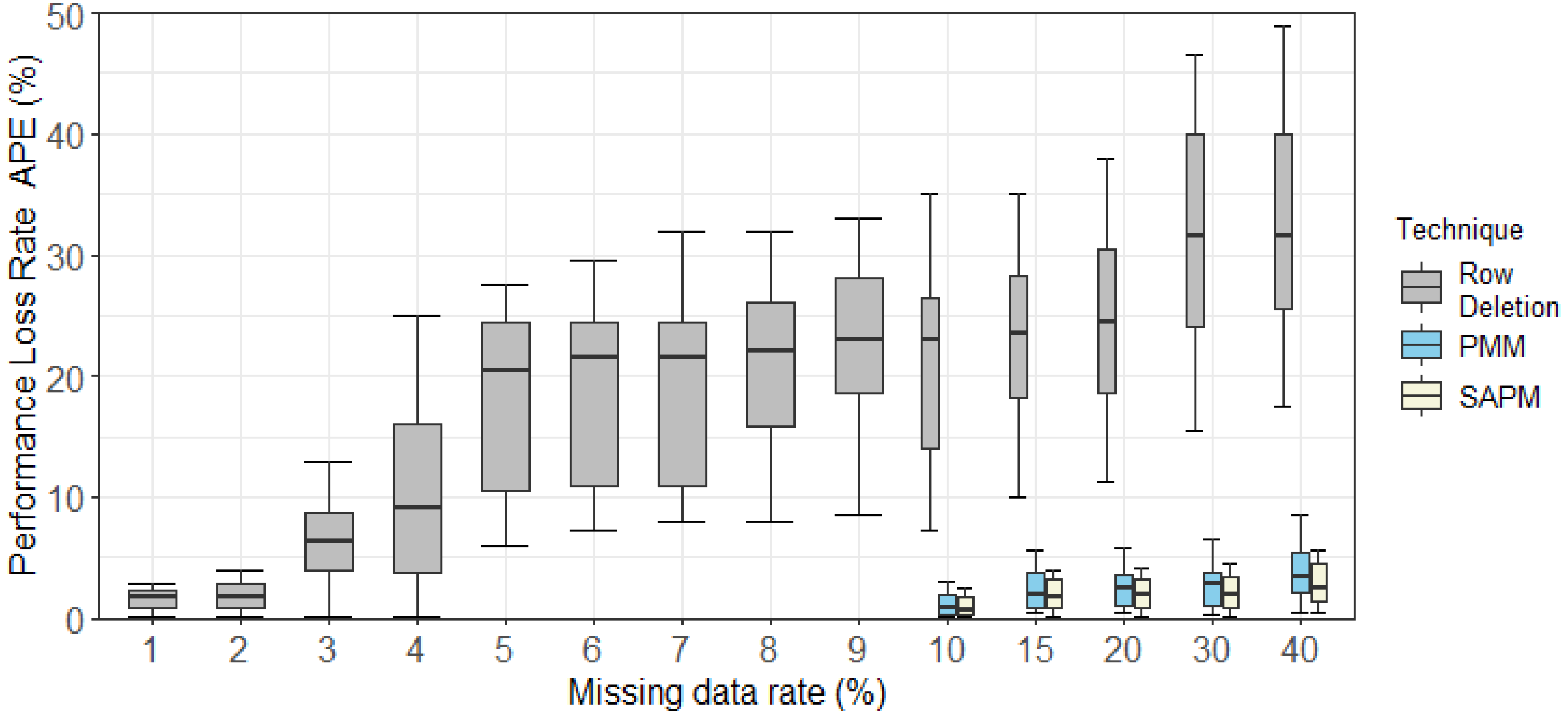
Results - Data integrity effect on PLR analysis

- Linear PLR was estimated by Ordinary Least Squares (OLS)
- 5-year PV dataset with continuous missing power measurements



Row deletion introduces a bias in the PLR calculation with the increasing missing data rate

Results - Data integrity effect on degradation analysis

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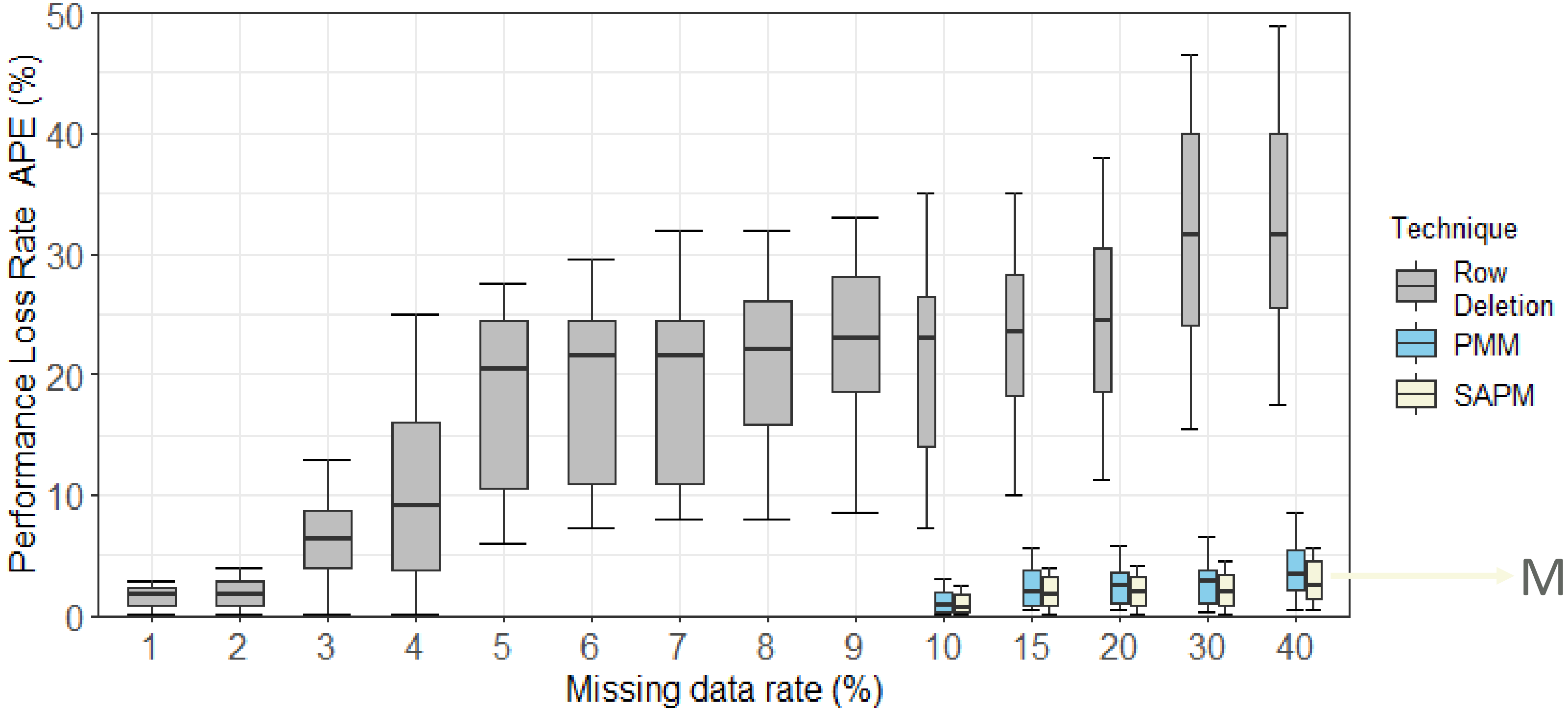
- 5-year PV dataset with continuous missing power measurements



Max APE of 5.69%

SAPM yielded more accurate results when compared to the PLR estimates of row deletion

Conclusions and Future Work

- DQRs were developed to ensure data validity and bridge the quantitative gap that exists in current practices
- The results demonstrated that datasets with:
  - missing data rates < 10%, can be reconstructed by row deletion
  - missing data rates > 10%, can be reconstructed by data inference techniques
- For PLR estimates, data inference techniques are recommended even at missing data rates as low as 3% (in the case of OLS)
- Electrical models yielded the lowest error among the investigated techniques
- Future work will focus on determining the impact of invalid data and reconstruction routines on additional performance indices

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Thank you for your attention

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